

Three Essays on Product Acquisition Management in Closed-Loop Supply Chains

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To my parents

Summary

One of the major global problems is the rapidly growing overconsumption of our finite natural resources. To overcome this problem, new sustainable business ideas like product recovery are becoming increasingly important. The main goal of product recovery firms is to sustain the value of already used goods in some form. This thesis examines some current challenges in the acquisition process of businesses with a focus on product recovery. The first essay investigates how a recovery firm collects the used products from individual holders in an optimal way. To be profitable, the firm has to balance the effort of the product holders to return their products with the respective acquisition costs resulting from the implemented collection network and the acquisition fee. The key result is achieved by a comparison of two currently applied strategies and shows the additional benefit of having a pricing strategy which differentiates by the quality of the used product. The second essay examines the optimal quality grading strategies of a recovery firm and an individual product holder who decides on returning his used product. A product holder has an incentive to grade the used product as being better than it is because of the higher achievable acquisition price, whereas the firm can increase the profit margin by downgrading the product. In short, the firm has to balance the risk of a rejection against the additional gain by downgrading the product quality. Here, one key result is that our model-based grading strategy has a great improvement potential in comparison with a currently applied strategy of a recovery firm. The third essay analyses the decision of a recovery firm to accept offered batches of used products from the B2B market. As the capacity management of processing individual product returns is a challenging task because of high volatilities in the return volumes, a firm can smooth capacity utilization by acquiring B2B returns. The key finding is that time-dependent effects can have a strong impact on the profitability of this capacity lever.

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Chapter 1

Introduction

One of the major global problems is the rapidly growing overconsumption of our finite natural resources which are crucial for life on Earth. Additional multipliers of this problem include, for example, the fast economic growth of emerging countries like China and the short life cycles of most of the technological products in the industrialized countries. The already observable consequences are climate changes, enlarging areas for landfilling, and the rising prices for resources as a result for their scarcity.

In order to overcome or to reduce this problem, new sustainable business ideas like product recovery are becoming increasingly important. The main goal of product recovery is to sustain the value of already used products in some form. To this end, recovery firms operate so-called *Closed-Loop Supply Chains* (CLSC), which “focus on taking back products from customers and recovering added value by reusing the entire product, and/or some of its modules, components, and parts” as defined by Guide and Wassenhove (2009). Thus, recovery firms generate profits without the production of new goods. As this life cycle expansion is an effective method of avoiding landfilling, the business of product recovery is commonly accepted as a sustainable solution for handling used and end-of-life products.

One of the essential challenges of CLSC is the management of the supply of used products from customers. The corresponding field of research is named in the literature as *Product Acquisition Management* (Guide and Jayaraman, 2000). This dissertation examines current issues in this context.

The economic potential of CLSC has been approved in several studies. With respect to the remanufacturing industries, a recent study is from the United States International Trade Commission (USITC, 2012). They discovered that during the period 2009 to

2011, the production of remanufactured goods grew by 15 percent to at least \$43 billion in the United States. This significant and rapid growth of these industries is achieved, for example, by opening up new acquisition and reselling markets or by developing completely new business fields.

During the last five years, we have carried out several projects with product recovery firms. These projects have revealed recent business challenges that arose in the context of product acquisition management. This dissertation introduces some of these business developments and investigates three new challenging issues of CLSC¹. To this end, this dissertation consists of three essays, which can be read independently.

Chapter 2 presents the first essay, which is a joint work written with Moritz Fleischmann. In this study, we investigate the interplay of the acquisition pricing strategy with the collection network design of CLSC. The key research question is: What is the best strategy to incentivize product holders to return their used products? Our research is motivated by observing two different strategies in the current practice of collecting used electronic devices, like mobile phones, tablets, and MP3 players. In the first strategy, the grading of the used products is operated in a centralized facility. Thus, the grading and afterwards the final acquisition price offer are carried out after the physical transportation of the used products to this specific facility. In the second strategy, the grading is decentralized at several collection sites to which the product holders can bring their used products. Here, they receive an exact acquisition price offer for handing in their products. Motivated by these observed structural differences, we raise the following questions: What are the benefits of each collection strategy, respectively? Furthermore, under what circumstances can one strategy dominate the other?

We answer these questions by describing the structural properties of both strategies, using a continuous approximation model. The model combines individual customer return behaviour, pricing strategies, and network design issues. We determine the optimal acquisition prices and their respective collection quantities for each strategy. By comparing both strategies, we determine the value of acquisition price differentiation in CLSC. This value defines the major benefit of a decentralized strategy. From an operational perspective, a decentralized grading strategy achieves a better quality ratio in the collected products which may outperform the centralized grading approach.

In Chapter 3, the second essay (also a joint work with Moritz Fleischmann) investigates the decisions of the recovery firm and the individual product holder in the acquisition

¹In the following chapters, we also use the equivalent term reverse supply chains instead of CLSC.

process. Many recovery firms have moved to a quality-dependent process for the acquisition of used products. To this end, product holders have to give upfront quality statements and will be offered quality-dependent acquisition prices for their used devices. Our interest is in identifying the product assessment strategy which optimizes the achievable profit from a product submission. Thus, our explicit research question is: How should a recovery firm act optimally in the acquisition process of individual product returns?

To answer this question, we develop a sequential bargaining model with complete information which describes the acquisition process in detail. We determine the optimal assessment strategies of the product holder and the recovery firm. We relax the assumption of complete information about the residual value of the holder of the used product and analyse the trade-off of the recovery firm when deciding on the counteroffer option. A data set consisting of nearly 60,000 product acquisitions of a recovery firm is used to approximate the product holder's behaviour. By comparing the benefits of an optimal counteroffer decision with the applied strategy of the recommerce provider, we find valuable improvements which affect the profitability of the recovery firm's acquisition process.

Chapter 4 presents the third essay, which considers the capacity management in the context of product acquisition. The research is motivated by a practice collaboration with a recovery firm in Germany which has started to acquire batches of used products from e-commerce providers (B2B). Capacity management is a challenging task when processing individual product returns (B2C) as specific events such as Christmas or the releases of new products cause high volatilities in the return volumes. To this end, the additional acquired products from the B2B market are used to achieve high capacity utilization in times when the individual return volume is low. The key research question of this research project is: Which batch offers shall a recovery firm accept or reject, respectively?

To reach an answer to this question, we explore the B2B acquisition market and analyse the underlying business decision about the acceptance or rejection of an offered batch. We show the current industry approach for this decision and identify additional time-dependent factors which have an impact on the profitability of this capacity lever. We use a basic scheduling model to capture these factors. By applying the model in a broad numerical study, we reveal the significant impact of time-dependent costs on the acceptance decision of a recovery firm. Additionally, we show the underlying complexity

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of this decision in selected scenarios.

All proofs for the defined propositions can be found in the appendices at the end of this dissertation. The references from all chapters are collected in one bibliography.

Chapter 2

Value of Acquisition Price Differentiation

with Moritz Fleischmann¹

Abstract

The quality of returned products may vary greatly, depending on their previous usage. Since the remanufacturing of products in good condition is more economically rewarding for the remanufacturer - and since even for non-remanufacturable products the value that can be extracted from their parts or materials may depend on the products' quality - it seems logical to acquire used products of different quality levels at different prices.

However, acquisition price differentiation requires the product quality to be revealed, i.e. the products are graded before their actual acquisition. We observe two different approaches in current practice. The first one is a decentralized system with several collection sites to which the customers can bring their used products. After a short grading procedure, they receive a specific acquisition price offer for their products, which they can accept or decline directly. The second setting is a reverse logistics system with a centralized grading facility. The final grading is conducted after shipping the used

¹The research presented in this chapter is based on the paper “The Value of Acquisition Price differentiation in Reverse Logistics”, coauthored with Moritz Fleischmann.

products to this specific facility.

Motivated by these empirical observations, we compare the two strategies with the help of a continuous approximation model. We derive analytical expressions for the optimal pricing and network density decision and show that, in addition to the other factors discussed in the literature, acquisition price differentiation can be a reason for decentralizing the reverse logistics network, if the product quality is uncertain. Furthermore, we illustrate our results with a numerical example.

2.1 Introduction

Since remanufacturing products in good condition is more economically rewarding for the remanufacturer, it seems logical to adapt a quality-dependent pricing strategy for the acquisition of used products (Guide et al., 2003). In our work, we name this pricing strategy acquisition price differentiation (APD). APD requires the product quality to be revealed, i.e. the products are graded before their actual acquisition. As a result, the implementation of APD has a major impact on the design as well as on the operating costs of a reverse logistics network and therefore also on the specific hand-in decision of the product holders. Our work deals with this specific interplay and shows the value of APD by comparing this pricing strategy with a quality-independent pricing strategy.

One of the major environmental problems globally is the overconsumption of materials in industrialized countries, which requires huge volumes of resources and produces vast quantities of pollutants and waste (Esty and Winston, 2006). The fast economic growth of emerging countries like China and India and their consequent change in lifestyles will lead to a further increase of the problem. The consequences of this problem can already be recognized today, for example by the enlarging areas for landfilling and the rising prices for resources as a result of their scarcity.

Due to these developments, new business ideas like product recovery are becoming increasingly important. The business of product recovery is not the production of new goods; instead, profits are generated by acquiring used goods and reselling them in some form. Thus, product recovery organizations operate so-called reverse supply chains, which are generally accepted as a sustainable solution for handling used and end-of-life products, because life cycle expansion by remanufacturing or recycling used products, for example, is an effective method of avoiding landfilling, reducing waste, and generating new resources (Quariguasi-Frota-Neto and Bloemhof, 2012).

Reverse supply chains face several additional business challenges compared with traditional forward supply chains (Guide et al., 2003). On the sales side, in general they have to offer the used products at lower reselling prices than their new counterparts, as customers are less willing to pay for used products. On the supply side, they face uncertainties regarding the quantity and quality of the returns. While the quantity uncertainty can be steered by appropriate buy-back prices, the quality aspect has a major impact on the recovery effort, and thus determines the achievable yield. These issues arise because individual product holders with different use patterns serve as suppliers, resulting in a very small distinction between “earning” and “losing” money in these industries.

Current practice shows two different approaches to the acquisition of small electronic devices, like mobile phones and MP3 players. The first one is a reverse logistics system with a centralized grading facility. Here, the grading and afterwards the final acquisition price offer are carried out after the physical transportation of the used products to this specific facility. Then the product holder can accept or decline this offer, which results either in the payment of the acquisition price or the transportation of the product back to the product holder. The second setting is a decentralized system with several collection sites to which the product holders can bring their used products. After a short grading procedure, they receive an exact acquisition price offered for handing in their products, which they can accept or not directly.

One example of the first centralized grading system is the current collection and recovery network for used mobile phones of *zonzoo*. On its website (www.zonzoo.de), a product holder selects the cell phone model he or she wants to sell, as well as the condition of the phone, and is then offered a provisional price. After accepting the offer, the cell phone is sent by mail to *zonzoo*. When the cell phone arrives, it is tested and compared with the product holder’s description. If the description fits the actual condition, *zonzoo* transfers the money to the product holder; otherwise, the product holder is offered a new, lower price. If the product holder does not accept the new offer, the product is sent back under the condition that he or she pays for the shipping costs.

To make the service easy to use for the product holders, *zonzoo* and other online providers for product recovery only differentiate between two quality categories, namely “functional” and “non-functional” cell phones. Functional means that the cell phone can be turned on and off, the display is working, and there is no significant external damage. The battery has to be included and has to be functional, too. Despite this

very simplified grading policy, only 90 per cent of the mobile phones handed in result in a payment for the product holder (Schuster and Thürmer, 2010). Most likely, this number would even be significantly smaller if the product holders did have to pay for sending back the mobile phones. Another disadvantage for the product holder is that the whole transaction procedure until the payment takes about two to four weeks.

One recent example of the second decentralized system is the “ecoATM Automated eCycling Station”. The ecoATM is a machine the size of a normal ATM, capable of automatically valuing used items, such as mobile phones, MP3 players, digital cameras, and other electronic devices (www.ecoatm.com). After the potential seller has inserted the item into the machine, the automatic testing process begins, including electrical and visual inspection of the device and its components. In order to determine the exact value of an individual item, each model is categorized into one of eight possible quality grades (Wilson, 2011). When this process is complete and the product holder agrees to the price offered, the ecoATM immediately collects the device and provides payment to the product holder. Each cell phone (of a certain model and in a certain condition) is priced by the ecoATM based on its value in the secondary markets.

The ecoATM has several advantages compared with acquiring used mobile phones over a website. For the product holder, inserting the cell phone into the machine might be quicker and easier than packaging and sending it or waiting at home for a pick-up. Also, while the product holder has to wait for payment for about two to four weeks and then receives the expected price in only about 90 per cent of the cases when selling mobile phones online, a product holder returning a device to an ecoATM is informed about the exact acquisition price, and then, if he agrees, receives payment immediately. This makes ecoATMs much more attractive to consumers.

A large difference exists in the availability of the two collection systems. While the availability of the centralized collection system depends only on the product holder’s access to the Internet and mail providers, the availability of the decentralized collection system is influenced by the investment in the number of collection points. Depending on the density of the collection points, a product holder has to travel, on average, a long or short distance to hand in his used device. Thus, the high investment costs for the collection points - the ecoATMs - might be an obstacle. The same trade-offs arise in decentralized systems in which the retailers are prompted to perform the grading activities. Since personnel have to be trained, specialized equipment has to be made available, and an incentive has to be provided to the retailers, the cost structure is

similar, and the difference from an automated system might not amount to much.

The goal of this paper is to investigate the benefits of the centralized collection system and the decentralized collection system, respectively. Furthermore, we want to identify the circumstances under which one collection strategy dominates the other. We summarize our problem as follows. We consider a collection area with continuously distributed product holders, owning used products of discrete quality classes. A product holder's hand-in decision depends on his individual quality perception of the product's residual value, the offered acquisition price, and the location-dependent travel effort required to hand in the used product. The centralized collection system offers one acquisition price for all product holders while the decentralized system stimulates returns with quality-dependent acquisition prices. In order to enable such an APD, the decentralized collection system faces fixed costs for operating the necessary collection points, whereas the centralized collection system uses the services of a mail provider and thus faces no investment costs for the collection. To capture the structural properties of each collection strategy and the product holder return behaviour and to make them comparable, we use a continuous approximation model. With the help of this model, we analyse the interplay between the APD and the cost of the underlying network design.

To summarize, our paper makes the following contributions:

- We describe the structural properties of a centralized and a decentralized collection system, respectively, using a continuous approximation model. Using this model, we combine individual customer return behaviour, pricing strategies, and network design issues and make the two collection systems comparable.
- We determine the optimal acquisition price(s) and their respective collection quantities in a centralized and a decentralized collection system. We argue that the major benefit of a decentralized collection system is its better quality ratio for the collected products.
- By comparing the two collection strategies, we reveal besides other effects the value of acquisition price differentiation (VAPD) in a reverse logistics collection system. Other revealed effects are caused by the delayed product holder payment and by the difference in the network density of the two collection systems.
- We illustrate by means of a numerical example that, depending on the severity of these effects, a decentralized collection system with APD can be more profitable

than a centralized collection system. Additionally, we show the influence of specific properties of the collected product on the design and profitability of a decentralized and a centralized collection system.

The remainder of the paper is organized as follows. In Section 2.2, we position our work in the research literature. Then we explain our key assumptions and the formulation of the model in Section 2.3. Section 2.4 contains the analytical results and Section 2.5 the numerical results. We summarize our main contribution in Section 2.6 and give directions for future research. All proofs are given in the appendix.

2.2 Literature review

So far, reverse logistics has proven to be a fast-developing new research field. Guide and Wassenhove (2009) is one of the latest review papers describing its past evolution. A comprehensive current overview of this field of research and its potential future development is given by Ferguson and Souza (2010). We have identified two major literature streams in reverse logistics, which we bring together in our work and to which we contribute: price differentiation and collection network strategies.

Price differentiation in reverse logistics has several analogies with the concepts of classical price discrimination in the microeconomics literature. In this research field, Pigou (1920) was one of the first to divide the different concepts into first-, second-, and third-degree price discrimination. In first-degree price discrimination, the selling price varies according to the willingness to pay of each customer. Thus, the producer can absorb the whole consumer surplus. Since a complete absorption of the consumer surplus is only achievable if the producer has full information about each individual consumer, this concept has low practical relevance. In second-degree price discrimination, the price varies due to differences in the product quantity or quality, e.g. larger quantities are available at lower unit prices. This widely used selling instrument needs only a minimum amount of consumer information and segments the market in an indirect way. In third-degree price discrimination, the segmentation is performed directly and each segment is priced separately. Thus, the selling price differs by customer segment. One famous example is student or senior discounts.

The use of quality-dependent acquisition prices in a reverse logistics, which we named in our paper acquisition price differentiation (APD), is quite similar to the classical price discrimination approaches. The main difference is that the focus is now on the supply

market, which is differentiated by the quality of the used products. APD segments the acquisition market according to the quality of the offered used products in the same way that classical price discrimination segments the demand market by willingness to pay.

Guide and Wassenhove (2001) were among the first in the reverse logistics literature to note that firms can control the quality of product returns. They mention the change at *ReCellular*, a cell phone remanufacturer, from a system of buying mobile phones of unknown quality in bulk to setting prices for a certain quality level. Guide et al. (2003) expand upon this notion and were the first to assume quality-dependent prices in the acquisition process of mobile phones. Due to their assumptions of discrete quality classes, their results are similar to the results of classical third-degree price discrimination. The optimal acquisition prices lead to marginal costs for each quality class equalling their marginal revenue.

Guide et al. (2003) assume that *ReCellular* can buy from suppliers who have already graded the used mobile phones into six different quality grades. Consequently, the grading process is neglected in their analysis, and as a result, *ReCellular*'s suppliers are facing the risk of handling the quality uncertainty of the returned products. The assumption of quality-dependent pricing is also relaxed in subsequent research that reconsidered the ReCellular case. Robotis et al. (2005) and Jayaraman and Luo (2007) assume that ReCellular sorts and grades the mobile phones after acquiring unsorted lots.

Another important work in the acquisition price differentiation stream is by Ray et al. (2005). They analyse trade-in rebates in the automotive market and treat quality as age-dependent, in contrast to usage-dependent, and assume that the exact age is known. Then they compare the potential of age-dependent, age-independent, and uniform pricing. Interestingly, the age-dependent pricing strategy causes continuous quality differentiation with full information about the used products. This results in a setting that is analogous to classical first-degree price discrimination.

There are many subsequent research papers that build on the work of Guide et al. (2003) and Ray et al. (2005), for example Karakayali et al. (2007), who determine optimal acquisition prices for remanufactured parts for different reverse channel structures of an OEM, or Zhou and Yu (2011), who integrate APD with the inventory management decision. Nevertheless, the main focus of these papers is on APD and they ignore both the related operational costs for enabling price differentiation and the specific customer return behaviour. Our work contributes to this literature stream by considering these issues and by integrating the specific interplay of APD with the costs of the underlying

network design into the analysis.

Due to this interplay, our work is also related to the collection strategy and network design literature. A current review is given by Aras et al. (2010), who also identify the “drop-off strategy” and the “pick-up strategy” as the two predominant collection methods in practice. Their drop-off strategy corresponds with the decentralized collection system introduced above, whereby product holders hand in their used products at collection points - the ecoATM stations - after a specific travel effort to reach these locations. The analogy for the centralized collection system depends on the mail service provider used for the shipments to the grading facility. There are central collection systems in which the product holders have to bring the parcels to the mailbox locations. In other systems, the parcels containing the used products are picked up from the product holders’ homes. Thus, depending on the specific mail service provider, the centralized collection system uses either a drop-off or a pick-up strategy.

Aras et al. (2010) and the affiliated working paper (Boyaci et al., 2009) analyse the trade-off between the transportation costs in the pick-up strategy and the financial incentives that have to be offered to end-users in order to return used products actively in the drop-off strategy with the help of a continuous approximation model. They consider quality-independent returns and thus do not differentiate acquisition prices. One of their results is that a high density of potential returns in an area favours the pick-up strategy because the transportation costs will be lower due to shorter distances. Our paper uses a similar model formulation for the comparison of the centralized and the decentralized collection system, and we contribute to this stream by introducing APD into the pricing decision.

There are several other papers in the collection strategy and network design literature that analyse the trade-offs of centralization and decentralization. Especially, in the context of decentralized grading activities, researchers have identified two different drivers for decentralization. The first one was investigated by Blackburn et al. (2004) and Guide et al. (2006). They observe that if the used products have a high marginal value of time, a less time-consuming decentralized grading set-up can be more beneficial than a cost-efficient slower one. These high marginal values of time are common, e.g. for most commercial returns in the electronic goods industry. Another driver was introduced by Tagaras and Zikopoulos (2008). They illustrate the trade-off between additional grading costs (at the collection sites) versus reduced transportation costs (to the central facility) as a driver. We contribute to their research by identifying APD as an additional driver

for a decentralized grading system to exploit quality uncertainty.

2.3 Model

2.3.1 Assumptions

In the following, we present our model assumptions and provide a short discussion.

1. Assumption: *The collection system is designed and operated separately from the new-product forward distribution system.*

Our setting consists of a product recovery organization that does not manufacture new products. It generates profits solely by acquiring and reselling used products. Therefore, we do not consider how and for which prices the products have reached the customers.

2. Assumption: *The used products under consideration for collection can be classified into i quality classes.*

Different use patterns in time and intensity result in used products with wide quality differences. In this work, we assume that these quality differences can be aggregated into a finite number of discrete classes, as in Guide et al. (2003). It is noteworthy that the number of quality classes can be driven by remanufacturing costs for each quality class (the quality perception of the collector) or by the quality perception of the product holder. A specific quality attribute can for example affect only the residual value of the product holder without having any impact on the remanufacturing costs or vice versa. In the following, we introduce further assumptions on the quality perception of the collector and the product holder, respectively.

Quality perception of the collector: *The collector faces product quality-dependent remanufacturing costs r_i for each returned product of quality i .*

The remanufacturing² of the used products requires an effort that is dependent on the specific quality class. High-quality returns of a mobile phone type need for example only simple surface cleaning and data deletion, while low-quality returns of the same mobile phone type require for example the additional replacement of individual keys, a new battery, etc.

Quality perception of the product holder: *(i) Product holders have a utility of not returning the product, which is dependent on the product quality i .*

²We use the term remanufacturing as the major term for product recovery operations, which also include refurbishing and recycling activities.

In general, the product holder has some knowledge about the quality of his product, which influences his perception of the residual value. In the case of a used mobile phone, a product holder knows his use intensity exactly, which is accompanied by a smaller or larger amount of physical damage, e.g. if the phone has been dropped. Other examples are that the phone may have been exposed to moisture, may not be fully functional, etc.

(ii) *For a randomly selected product holder, this utility is assumed to be uniformly distributed in the interval $[0, U_i]$, due to the heterogeneity of the product holders.*

As we consider all product holders of a specific product type, their perception of a specific quality attribute of their used products is heterogeneous. We approximate this heterogeneity with the help of a uniform distribution, which allows analytical tractability and is common in this research context (Aras et al., 2008; Aras and Aksen, 2008; Ray et al., 2005; Wojanowski et al., 2007; Boyaci et al., 2009; Karakayali et al., 2007). In our analytical model formulation, we use a customer quality perception heterogeneity interval $[0, U_i]$, like Aras et al. (2008) and similarly to Boyaci et al. (2009), where U_i represents the maximum residual utility level for a product holder of a product with quality i . Introducing a specific lower bound for the uniform distribution would result in more case distinctions in the analytical part of this paper without providing any further managerial insights. We relax the assumption in the numerical part of this paper by using a lower bound for each quality class.

3. Assumption: *Each product holder makes an individual decision to return a used product based on his travel effort x and the offered acquisition price a_i .*

We use a customer choice model in which the used product will be handed in if the utility of returning the product is higher than the perceived residual value u_i . We assume the following linear relationship as the product holder's utility for handing in the product:

$$h \cdot a_i - k \cdot x. \quad (2.1)$$

Here the coefficient k weights the travel effort x and h weights the monetary benefit of the acquisition price. The linear relationship results in a return function that is linearly increasing in the acquisition price. Atas and Souza (2013) provide two empirical examples of such a collection cost progression, which is also assumed by Ferguson and Toktay (2006).

4. Assumption: *The product holders of class i are uniformly distributed across the considered area with a product density of ϕ_i .*

The continuous approximation methodology first introduced by Daganzo (1999) has

found many applications in the forward and reverse supply chain literature (Fleischmann, 2003; Wojanowski et al., 2007). The key assumption of continuously distributed product holders is commonly further narrowed down to a uniform distribution, for analytical tractability. We follow this approach. Assuming a uniform distribution is reasonable if the collection area is not too large. For numerical calculations, the uniformity assumption can be relaxed.

5. Assumption: *The collector faces a market price m for the remanufactured products.*

Most product recovery facilities sell their remanufactured products in foreign markets where the sold amounts have a negligible impact on the market price. As our focus is on the collection of the used products, we assume a fixed market price for a single output quality. Thus, the collector is a price-taker on the reselling market. In the following, we calculate with a quality-dependent margin (p_i) which is the market price reduced by the related remanufacturing costs ($p_i = m - r_i$). Multiple output qualities lead to the same results if they are known for each quality class because their influence can then be captured by adjusting the remanufacturing cost.

6. Assumption: *The decentralized and centralized collection systems use different pricing strategies.*

Centralized collection system: *The collector offers the same acquisition price (a) to all product holders as a financial incentive to entice returns. Due to the delayed and uncertain payment, product holders discount these prices by η .*

As discussed in Section 2.1, most of the centralized collection systems differentiate only between functional and non-functional quality, to facilitate the product holder's grading process. Hence, differentiation in the quality of the used products is strongly limited in these collection systems. Furthermore, non-functional electronic devices have a low recovery value because in most cases recycling is the only option for them. Independently of the collection system, this recovery option is the least profitable one. Our focus is on the functional used products, which achieve an important margin for the collection systems. Thus, we neglect the non-functional products and assume that a central collector offers only one acquisition price for functional products.

One of the main observed disadvantages of the centralized collection systems arises from the lengthy grading process because the product holder will not be paid until the final grading of the product is finished. Consequently, the product holder's waiting time for his payment is at least two to four weeks, depending on the specific utilization of the

central grading facility. We assume that the waiting time is anticipated by the product holder. Thus, he discounts the monetary utility of the acquisition price by the parameter η .

Decentralized collection system: *The collector offers an acquisition price (a_i) dependent on the product quality i as a financial incentive to entice returns.*

In the decentralized collection system, exact quality grading is performed before the final acquisition price offer. Hence, there are no limitations in the price differentiation for the decentralized collector.

2.3.2 Formulation

This section describes our model formulation. We first concentrate on the decentralized collection system and derive its return and profit densities from the customer choice model. We then repeat these steps for the central collection system. Table 2.1 summarizes the notation.

Symbol	Description
\mathcal{I}	Set of quality levels $\mathcal{I} = \{1, \dots, I\}$
a_i	Acquisition price for product of quality i
h	Weight for monetary utility
k	Weight for travel effort per distance unit
u_i	Customer residual product value of quality i
p_i	Margin for a collected product of quality i ($p_i = m - r_i$)
d	Radius of the area served by a collection site
x	Product holder's travel distance
ρ_i	Return density of products of quality i
Pr_i	Probability that a customer hands in his used product of quality i
ϕ_i	Density of used products with quality i in the market
F	Fixed costs for installing and operating a decentralized collection site

Table 2.1: Notation

Decentralized collection system

In the decentralized collection system, the product holders have to travel the distance to the collection points. Consequently, they will perceive a travel effort when handing in their used products ($k \cdot d \geq 0$). From Assumptions 2 and 3 we can derive the individual

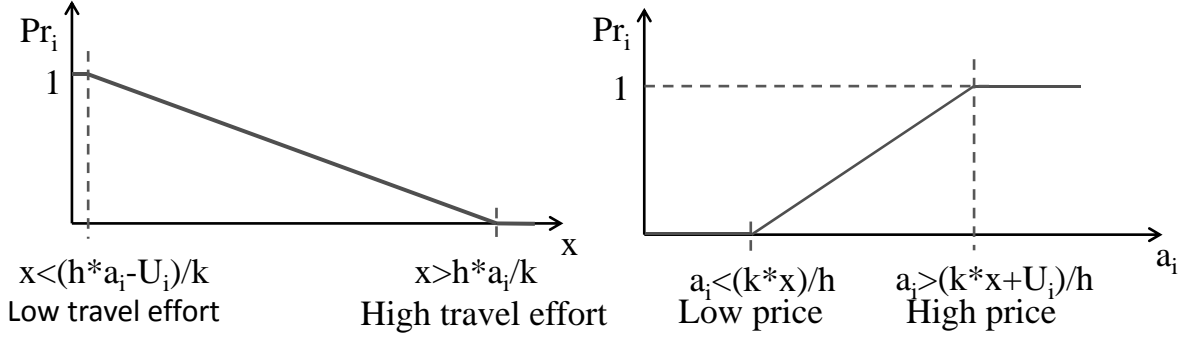


Figure 2.1: Return probability dependent on travel distance x (left) and acquisition price a_i (right)

product holder return probability for a used product of quality i for an acquisition price a_i at a distance x as

$$Pr_i(x, a_i) = Pr_i(h \cdot a_i - k \cdot x - u_i > 0) = \begin{cases} 1 & 0 \leq x < \frac{h \cdot a_i - U_i}{k} \\ \frac{h \cdot a_i - k \cdot x}{U_i} & \frac{h \cdot a_i - U_i}{k} \leq x \leq \frac{h \cdot a_i}{k} \\ 0 & x > \frac{h \cdot a_i}{k} \end{cases} \quad (2.2)$$

Figure 2.1 illustrates the piecewise-defined probability return function (2.2). We see that if the offered acquisition price is high (low) and the travel effort is low (high), then all (no) product holders will hand in their used products. Between these two bounds only a fraction of the products will be returned due to the heterogeneity of the product holders. With the help of the probability return function, we can calculate the expected return function of a circular collection area, dependent on the offered acquisition price a_i and the collection area radius d . The use of a set of circles to approximate the considered area is a common approach in this context (Wojanowski et al., 2007; Fleischmann, 2003). A simple scaling of this return function with the collection surface results in a density function for the return quantities. This function is used to define the collector's profit as the profit per area served. This is helpful for the comparison of the two collection strategies.

The circumference of a circle at a distance x from the collection point is $2\pi x$. By multiplying this value with the product density of quality ϕ_i and the probability function $Pr_i(x, a_i)$, we obtain the expected number of product holders who will decide to hand in their used products at a distance of x from the collection point. Integrating the resulting function over x and dividing by the collection area surface (πd^2) results in the following

return density function:³

$$\begin{aligned}
 \rho_i(d, a_i) &= \frac{1}{\pi d^2} \int_0^d 2\phi_i \pi x Pr_i(x, a_i) dx \\
 &= \frac{1}{d^2} \left(\int_0^{(\frac{ha_i - U_i}{k})^+} 2\phi_i x dx + \int_{(\frac{ha_i - U_i}{k})^+}^{\min(d, \frac{ha_i}{k})} 2\phi_i x \left(\frac{ha_i - kx}{U_i} \right) dx \right) \\
 &= \begin{cases} \frac{\phi_i}{U_i} \left(ha_i - \frac{2}{3}kd - \frac{k}{3d^2} \left(\frac{ha_i - U_i}{k} \right)^3 \right) & d \leq \frac{ha_i}{k} \\ \frac{\phi_i}{U_i} \left(\frac{(ha_i)^3}{3(kd)^2} - \frac{k}{3d^2} \left(\frac{ha_i - U_i}{k} \right)^3 \right) & d > \frac{ha_i}{k}. \end{cases} \quad (2.3)
 \end{aligned}$$

We see that the return density function is dependent on the relation of the travel effort and the offered acquisition price. In the first case ($d \leq \frac{ha_i}{k}$), at least a fraction of the product holders return their used products in the whole collection area. In the second case ($d > \frac{ha_i}{k}$), there are regions in the collection area where no returns are initiated, due to the high travel effort related to the offered acquisition price.

With the return density function and a as the acquisition price vector ($a = (a_1, \dots, a_I)$), the profit density function of the decentralized collector is as follows:

$$\Pi^d(d, a) = \sum_i ((p_i - a_i) \rho_i(d, a_i)) - \frac{F}{d^2 \pi}. \quad (2.4)$$

The first part of the function describes the summed-up margins per area of each quality class i , and the second part denotes the costs for operating a collection point (F), scaled by the size of the collection area ($d^2 \pi$).

It is clear from (2.4) that it is not beneficial to offer acquisition prices that are higher than the achievable margin, and thus the bounds for the acquisition prices are $0 \leq a_i \leq p_i$ for all the quality classes. Furthermore, we restrict our attention in the following analytical part to cases in which $ha_i \leq hp_i \leq U_i$. Large U_i values are reasonable as some of the used products are still in regular use by the product holders and thus their residual value is still very high. Low p_i values can be explained by the low prices for the remanufactured products in the reselling markets. This assumption simplifies the return density function (2.3) as $(ha_i - U_i)^+$ vanishes.

³We use x^+ as an abbreviation for $\max(0, x)$.

Centralized collection system

In the centralized collection system, the collector offers only a single acquisition price (a) for all the quality classes. Additionally, this price is discounted by the product holders by η . The individual customer return probability for a product of quality i for an acquisition price a can be derived analogously to the decentralized collection system. The hand-in effort of the product holders is described again by the weighted travel distance kx . In the centralized collection system, this travel effort is dependent on the distance of a product holder to the next mailbox where he can drop off his packed used device. The individual return probability for the centralized collection system is therefore as follows:

$$Pr_i(x, \eta a) = Pr_i(\eta \cdot h \cdot a - k \cdot x - u_i > 0) = \begin{cases} 1 & 0 \leq x < \frac{\eta \cdot h \cdot a - U_i}{k} \\ \frac{\eta \cdot h \cdot a - k \cdot x}{U_i} & \frac{\eta \cdot h \cdot a - U_i}{k} \leq x \leq \frac{\eta \cdot h \cdot a}{k} \\ 0 & x > \frac{\eta \cdot h \cdot a}{k} \end{cases} \quad (2.5)$$

Subsequently, the return density can be calculated analogously to (2.3). In the centralized collection system, we denote the collection area radius of a mailbox as \tilde{d} and therefore the return density for a quality class i is $\rho_i(\tilde{d}, \eta a)$.

Dependent on the mail service provider, some centralized collection systems use a pick-up strategy instead of a drop-off one (Aras et al., 2010). In this case, the collection is made via a pick-up at the product holders' homes. When using our model for a pick-up strategy, we have to interpret and scale $k\tilde{d}$ as the product holders' effort in waiting for the pick-up.

After the product holders have dropped their devices into a mailbox or an ecoATM, these will be shipped to a central product recovery facility for the quality-dependent remanufacturing processes. In the centralized collection system, the grading is also conducted at this facility. For these shipments, the centralized collector uses the network of a mail logistics provider and faces no fixed costs for installing and operating any collection points, in comparison with the decentralized collector. We assume that the differences in the costs occurring from the different transportation distances to the central product recovery facility as well as for the final grading are negligible or can be considered by an adjustment of the fixed and operating costs (F) of the decentralized collector. Consequently, the profit function of the centralized collection system (Π^c) is

as follows:

$$\Pi^c(\tilde{d}, a) = \sum_i (p_i - a) \rho_i(\tilde{d}, \eta a). \quad (2.6)$$

2.4 Analysis

In this section, we start with the analytical derivation of the optimal acquisition prices in the decentralized collection system and the centralized collection system, respectively. Then we analyse their respective collected quantities and give a detailed comparison of both profit density functions, which enables the isolation of the value of APD from the other effects. We close the analytical part of this study with the derivation of the optimal network density of a decentralized collection system.

2.4.1 Optimization of acquisition prices

Decentralized collection system

The collector of the decentralized collection system has to decide on the exact acquisition price he will offer for each quality class. In the described case of the ecoATM, the acquisition prices are updated automatically for all ecoATM stations via a network connection through which they can interrogate a central database (Wilson, 2011). Due to the quick adjustment of the prices of the used products, the pricing is categorized as a short-term decision.

Besides the pricing decision, the collector also faces the long-term decision about the density of the collection network. In the ecoATM case, he has to decide how many stations will be installed in the whole collection area. The number of stations determines the collection area radius of each station and therefore the travel effort of the product holders. In what follows we first focus on the pricing decision a_i and assume the network density d to be given. In Section 2.4.4 we show how the values of a_i and d can be determined simultaneously through an iterative procedure. We use this procedure in our numerical study in Section 2.5.

Proposition 1. *For a given network density d , the optimal acquisition price for products*

of quality i is given for the decentralized collector by

$$a_i^*(d) = \begin{cases} \frac{1}{2}p_i + \frac{1}{3}\frac{kd}{h} & d \leq \frac{3}{4}\frac{hp_i}{k} \\ \frac{3}{4}p_i & d > \frac{3}{4}\frac{hp_i}{k}. \end{cases}$$

Proposition 1 shows that the optimal acquisition price is dependent on the ratio of the collection area radius d and the specific margin for a collected product p_i . General insights for both cases are that the collector does not have to consider dependencies between the different quality classes due to the separate acquisition price for each quality class.

If $d \leq \frac{3}{4}\frac{hp_i}{k}$, it is beneficial for the collector to consider the network density (proximity to the customers) in the pricing strategy. We see that the optimal acquisition price consists of the basic monopoly price ($\frac{p_i}{2}$) and is increased with additional compensation for the travel effort ($\frac{kd}{3h}$).

If $d > \frac{3}{4}\frac{hp_i}{k}$, offering additional compensation for the travel effort is not profitable and the optimal acquisition price is at its upper bound ($\frac{3}{4}p_i$). In the context of mobile phones and other small electronic devices, especially non-functional devices that have to be recycled belong to this case because they provide relatively low margins (p_i). The collector will harvest the products of this class because he has already installed an operating collection system. Due to the fact, already mentioned in Section 2.3.1, that most centralized collection systems also distinguish between functional and non-functional products and set separate prices, we disregard the second case in the following analytical part of this paper.

Centralized collection systems

Considering the centralized collection system, we focus again on the short-term pricing decision because the collection area radius \tilde{d} is determined by the mail service provider who is responsible for the mail shipments.

Proposition 2. *For a given network density \tilde{d} , the optimal quality-independent acquisition price for the centralized collector is given by*

$$a^* = \begin{cases} \frac{1}{2}\frac{\sum_i \frac{\phi_i p_i}{U_i}}{\sum_i \frac{\phi_i}{U_i}} + \frac{1}{3}\frac{k\tilde{d}}{\eta h} & \tilde{d} \leq \frac{3}{4}\frac{\eta h}{k}\frac{\sum_i \frac{\phi_i p_i}{U_i}}{\sum_i \frac{\phi_i}{U_i}} \\ \frac{3}{4}\frac{\sum_i \frac{\phi_i p_i}{U_i}}{\sum_i \frac{\phi_i}{U_i}} & \tilde{d} > \frac{3}{4}\frac{\eta h}{k}\frac{\sum_i \frac{\phi_i p_i}{U_i}}{\sum_i \frac{\phi_i}{U_i}}. \end{cases}$$

We see that the optimal acquisition price a^* has the same structure as the optimal acquisition prices a_i^* of the decentralized collector. The main difference is that the optimal price is now dependent on the weighted average of the margins. The weight for each margin is the density of used products with quality i in the market (ϕ_i) divided by the diversity of the customer perception of quality (U_i). The ratio ($\frac{\phi_i}{U_i}$) describes the slope of the return function (see Equation (2.3)) and, thus, reflects the product holders' return behaviour for a specific quality class i . An increase in the acquisition price a results in more product returns for quality classes i with a high value of $\frac{\phi_i}{U_i}$.

In the first case of Proposition 2, the network density (proximity to the customers) again impacts on the pricing strategy. Again, it is beneficial to offer additional compensation for the travel efforts of the product holders.

The second case ($\tilde{d} > \frac{3}{4} \frac{\eta h}{k} \sum_i \frac{\phi_i p_i}{U_i} / \sum_i \frac{\phi_i}{U_i}$) describes again the upper bound for the optimal acquisition price. This case is negligible due to the fact that the networks of postal service providers tend to be very dense (\tilde{d} is very small). Universal Postal Union (2012) shows that for example in Germany the average collection area radius of a mailbox is about one kilometre.

2.4.2 Optimal acquisition quantities

Using the optimal acquisition prices, we determine the total return quantities (per surface area) for the decentralized Q^d and centralized Q^c collection systems:

$$Q^d := \sum_i \rho_i(d, a_i^*) = \sum_i \frac{\phi_i(3hp_i - 2kd)}{6U_i} \quad (2.7)$$

$$Q^c := \sum_i \rho_i(\tilde{d}, a^*) = \sum_i \frac{\phi_i(3h\eta p_i - 2k\tilde{d})}{6U_i}. \quad (2.8)$$

To compare the two quantities, we calculate the difference between Q^d and Q^c :

$$\begin{aligned} \Delta Q := Q^d - Q^c &= \sum_i \frac{\phi_i(3hp_i(1 - \eta) - 2k(d - \tilde{d}))}{6U_i} \\ &= \sum_i \frac{\phi_i}{U_i} \left(\frac{h}{2}(1 - \eta)p_i - \frac{k}{3}(d - \tilde{d}) \right). \end{aligned} \quad (2.9)$$

Interestingly, the research literature about third-degree price discrimination leads in general to the result that there is no effect of a discriminating pricing strategy on the

quantities sold (Schmalensee, 1981). In our setting, we see two effects on the difference in the collected quantities: first, a positive impact for the decentralized collection system due to the discounting of the payment by the product holders in the centralized collection system $(1 - \eta)$; second, a negative impact on the decentralized collected quantities due to the difference in the network density $(d - \tilde{d})$ as in most of the cases the collection area radius of the collection points - the ecoATM stations - will be larger than in the mailbox network $(d > \tilde{d})$. It is noteworthy that the positive impact of a decentralized collection system on the collected amounts in Equation (2.9) is dependent on the margin p_i , whereas the negative impact is margin-independent.

We examine this effect in more detail by comparing the quality ratio of the collected goods. Therefore, we determine the ratio of the return density of two different quality classes i and j and relate the ratio of the decentralized collection system to the ratio of the centralized collection system:

$$\begin{aligned} \frac{\text{Quality ratio decentralized collected goods}}{\text{Quality ratio centralized collected goods}} &= \frac{\rho_i(d, a_i^*)/\rho_j(d, a_j^*)}{\rho_i(\tilde{d}, \eta a^*)/\rho_j(\tilde{d}, \eta a^*)} \\ &= \frac{3hp_i - 2kd}{3hp_j - 2kd}. \end{aligned} \quad (2.10)$$

We see that the ratio of the collected amounts of quality i and j depends only on the relation of the margins p_i and p_j . Thus, if the margin of quality i is bigger (smaller) than the margin of quality j , the decentralized collection system collects relatively more (fewer) used products of the “better” (“poorer”) quality, compared with the centralized collection system. This superior quality ratio is one of the key benefits of a decentralized collection system since having “better” used products is a crucial factor in many reverse logistics industries.

2.4.3 Value of acquisition price differentiation (VAPD)

After analysing the pricing decision and the return quantities, we explore the structural properties of the profit function of the decentralized and centralized collection systems. To this end, we simply subtract both profit functions:

$$\Delta\Pi^* = \Pi^d(d, a^*) - \Pi^c(\tilde{d}, a^*). \quad (2.11)$$

In the first step, we disregard the effects resulting from the discounted payment and the difference in the network density. For this reason, we assume $\eta = 1$ and $d = \tilde{d}$. Recalculating Equation (2.11) with these assumptions leads to $\Delta\Pi^O$:

$$\Delta\Pi^O = \frac{h}{4} \frac{\sum_{i=1}^{I-1} \sum_{j=i+1}^I \frac{\phi_i}{U_i} \frac{\phi_j}{U_j} (p_i - p_j)^2}{\sum_{i=1}^I \frac{\phi_i}{U_i}} - \frac{F}{d^2\pi} \quad (2.12)$$

The second term in (2.12) defines the negative fixed costs for operating a collection point in the decentralized collection system, whereas the first term describes the positive effect of setting a separate acquisition price for each quality class. Consequently, the first term expresses the value of acquisition price differentiation (VAPD). We see that the variance of the margins p and thus the specific remanufacturing costs for each quality class have a great influence on the VAPD, besides the product holder's heterogeneity regarding size ϕ and perception of quality U .

In Section 2.2, we discussed the similarities between APD and classical price discrimination. Motivated by these findings, we compare the VAPD with the value of classical third-degree price discrimination in which the offered products are discriminated by the selling prices in the demand markets. In the classical setting, these markets differ in their price elasticities and have market-dependent variable costs. Interestingly, the VAPD has an analogous structure to that of the value of classical third-degree price discrimination. In the classical case, $\frac{\phi_i}{U_i}$ is replaced by the slope of the demand functions of a specific market segment and the specific profit margin for each quality class p_i is analogously a specific market-dependent variable cost. According to this analogy, APD contains the basic effects of classical price discrimination, which, in our setting, have a positive impact on the profitability of a decentralized collection system.

After having isolated the VAPD, we also include the effects of the delayed payment and the network density difference. The recalculation of (2.11) then leads to:

$$\begin{aligned} \Delta\Pi^* = & \frac{h}{4} \frac{\sum_{i=1}^{I-1} \sum_{j=i+1}^I \frac{\phi_i}{U_i} \frac{\phi_j}{U_j} (p_i^2 - 2\eta p_i p_j + p_j^2)}{\sum_{i=1}^I \frac{\phi_i}{U_i}} + \frac{(1 - \eta) \sum_i (\frac{\phi_i}{U_i} p_i)^2}{\sum_{i=1}^I \frac{\phi_i}{U_i}} \\ & - \frac{k}{3} (d - \tilde{d}) \sum_i p_i \frac{\phi_i}{U_i} + \frac{k^2}{9h} (d^2 - \frac{\tilde{d}^2}{\eta}) \sum_i \frac{\phi_i}{U_i} - \frac{F}{d^2\pi}. \end{aligned} \quad (2.13)$$

In comparison with (2.12), we see one equal term, one similar term, and three new terms. As we have already analysed the VAPD, we remove its effect by simple subtraction

and obtain the following three terms:

$$\begin{aligned}\Delta\Pi^N &:= \Delta\Pi^* - \Delta\Pi^O \\ &= \frac{h}{4}(1-\eta)\frac{\left(\sum_i \frac{\phi_i}{U_i}p_i\right)^2}{\sum_i \frac{\phi_i}{U_i}} - \frac{k}{3}(d-\tilde{d})\sum_i \frac{\phi_i}{U_i}p_i + \frac{k^2}{9h}(d^2 - \frac{\tilde{d}^2}{\eta})\sum_i \frac{\phi_i}{U_i}.\end{aligned}\quad (2.14)$$

The first term is positive and because of the main influence of η it can be interpreted as a discounted payment effect. The second term is negative (when assuming again that the network density of the decentralized collection system is smaller than the one of the postal service provider in the centralized case). Due to the main impact of the difference of the collection area radiuses, it can be interpreted as the network density effect. The third term is a mixture of the network density and the discounted payment effect and depending on the magnitude of these effects it can be positive or negative.

To summarize, we see that there can be an additional positive impact or a negative impact on the profitability of a decentralized collection system, due to the network density and discounted payment effects besides the general positive impact of acquisition price differentiation. We also see that the parameter k , which depends on the bulkiness of the used products to be collected, has a major impact on the network density effect. As our focus is on small electronic devices like mobile phones or laptops, the bulkiness k will be rather low, which reduces the network density effect.

In order to illustrate the influences of different parameters on the profitability of both collection systems, we provide several numerical examples in Section 2.5.

2.4.4 Optimal network density of the decentralized collection system

The following proposition shows the condition for the optimal network density of the decentralized collection system for a fixed set of acquisition prices (a) in an implicit equation.

Proposition 3. *For a fixed set of acquisition prices (a) with $a_1 \geq a_2 \geq \dots \geq a_I$, the optimal network density $d^*(a)$ is either infinite or $d^*(a) \leq \frac{ha_1}{k}$ and it satisfies the implicit*

equation

$$d^*(a) \doteq \left(\frac{3F/\pi - \sum_i \mathbb{1}_{\{ha_i/k < d^*(a)\}} \frac{(p_i - a_i)\phi_i h^3 a_i^3}{U_i k^2}}{\sum_i \mathbb{1}_{\{ha_i/k \geq d^*(a)\}} \frac{(p_i - a_i)\phi_i k}{U_i}} \right)^{\frac{1}{3}}. \quad (2.15)$$

Proposition 3 can be interpreted analogously to Boyaci et al. (2009), where it is shown for a single-quality, single-product collection network that reaching the upper bound in the pricing decision implies that the collection of the used product is not profitable. In our setting, all the quality classes of a used product contribute to the profitability of the collection system. As a result, a quality class of a used product whose weighted margin is lower than the optimal collection area radius is unprofitable in isolation. If for all quality classes the optimal collection area radius is higher than the weighted margin, then the whole decentralized collection system is unprofitable. In that case, the decentralized collector would choose $d^* = \infty$ and thus would achieve $\Pi^d = 0$.

Proposition 4. *The following algorithm converges to the jointly optimal acquisition prices a^* and network density d^* :*

1. Step: $d := 0$.
2. Step: Calculate $a := (a_1^*(d), a_2^*(d), \dots, a_i^*(d))$ using Proposition 1 and set $\hat{d} := d$.
3. Step: If $d > ha_i/k$ for all $i \in \mathcal{I}$, then set $d := \infty$. Otherwise, calculate d using Equation (2.15) as follows:

$$d = \left(\frac{3F/\pi - \sum_i \mathbb{1}_{\{ha_i/k < \hat{d}\}} \frac{(p_i - a_i)\phi_i h^3 a_i^3}{U_i k^2}}{\sum_i \mathbb{1}_{\{ha_i/k \geq \hat{d}\}} \frac{(p_i - a_i)\phi_i k}{U_i}} \right)^{\frac{1}{3}} \quad (2.16)$$

4. Step: If $d = \hat{d}$, then d and a are optimal. Otherwise, repeat Steps 2-4.

In the following section, we give a short numerical illustration of the analysed problem setting. Proposition 4 shows how we calculated the optimal acquisition prices a_i and optimal collection area radius d .

2.5 Numerical illustration

In this section, we illustrate the impact of key problem parameters on the profitability of a centralized and a decentralized collection system with the help of the developed continuous approximation model. We use a data set of the mobile phone remanufacturing industry from the literature. Our objective is to exemplify our analytical results and identify the strengths and weaknesses of the different collection systems.

2.5.1 Numerical data

We scale the monetary utility of the product holders to one ($h = 1$) and assume the collection radius of each mailbox for the centralized collection system to be one kilometre ($\tilde{d} = 1$), as is the case in Germany (Universal Postal Union, 2012). The decentralized collector operates a collection system with an optimal network density as described in 2.4.4. At the end of this section, we show the influence of a fixed network density.

To describe the quality classes of a used product, we use a data set of the mobile phone remanufacturing industry provided by Guide et al. (2003). Table 2.2 shows the data for the relevant remanufacturing costs r_i with their resulting margin⁴ (p_i) and the parameters of the return functions for each quality class i . As Guide et al. (2003) use a

Quality class i	1	2	3	4	5	6
Remanufacturing cost r_i	5.0	20.0	30.0	35.0	40.0	45.0
Intercept return function L_i	17.0	13.0	8.0	6.0	4.0	2.0
Slope return function ϕ_i/U_i	1.0	5.0	20.0	30.0	20.0	30.0
Margin for a collected product p_i	55.8	40.8	30.8	25.8	20.8	15.8

Table 2.2: Parameters describing the quality classes

minimal acquisition price, below which products of quality class i will not be returned, we also incorporate this lower bound into the following calculations. In our model, this results in a lower bound for the residual value of the product holders. Consequently, the product holders' residual value u_i is now uniformly distributed over the interval $[L_i, U_i]$.

One key problem parameter for both collection systems is the perception of the product holders's travel effort (k). The reverse logistics literature provides different parameters

⁴We use the optimized market price ($m = 60.8$) of the numerical illustration of Guide et al. (2003). Note that we assume a quantity independent fixed market price. We can calculate the margin for each quality class by $p_i = m - r_i$.

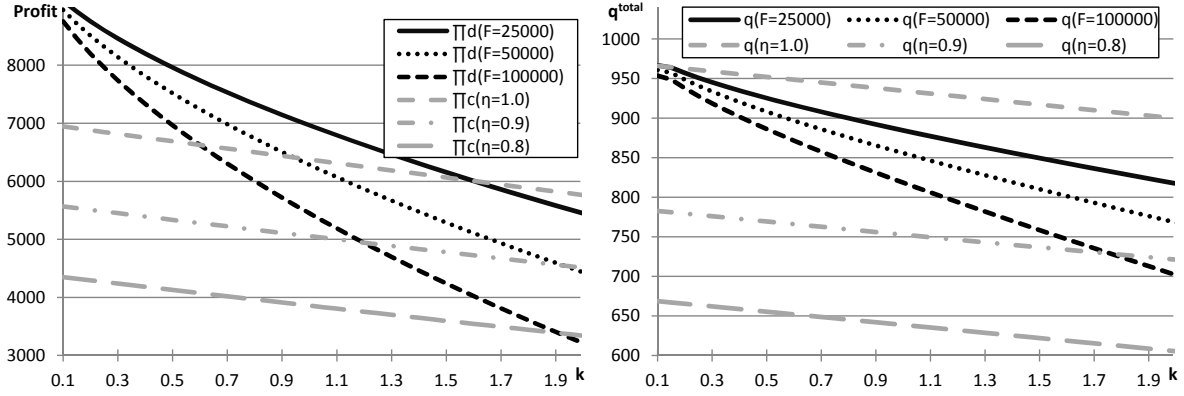


Figure 2.2: Impact of the key problem parameters on the profit (left) and total collected quantities (right)

for the weight of the travel effort. In the context of collecting used products from households, Wojanowski et al. (2007) use $0.3/km$.⁵ Aras and Aksen (2008) do not specify the background of their used products but assume $k = 1/km$. Boyaci et al. (2009) derive their used parameters from a WEEE collection report and generate $k = 1.3304/km$ for the perception of the travel effort of the product holders. In our setting, a low weight for the travel effort is appropriate as our focus is on the collection of small electronic devices with rather low bulkiness. We use a range of $[0.1;2]$ for k in the following numerical illustrations.

2.5.2 Impact of the key problem parameters

Figure 2.2 illustrates the achievable profits of a decentralized and a centralized collector, respectively, and their respective total collected quantities. In Section 2.4, we observed that the critical parameter for a decentralized collection system is the fixed cost for operating a decentralized collection point (F). Therefore, we illustrate the profit and quantities of a decentralized collection system for three different fixed costs values (25000, 50000, 100000). Analogously, for the centralized collector, we illustrate profit and quantities for three different values of the discounting of the payment η (1.0, 0.9, 0.8).

We see in Figure 2.2 that an increase in the weight of the travel effort k decreases the profit of both collection systems. Comparing the two systems, we observe that the profit and quantity decrease is much stronger for the decentralized collection system. This can

⁵Originally, they use $k = 3$ but scale the monetary utility to 10.

be explained by the difference in the collection network design and the resulting cost structures and is in line with the results in Section 2.4.2 and 2.4.3. On the one hand, the centralized collector uses the postal network with a rather high network density. Thus, the higher travel effort does not affect the customer return behaviour that greatly. On the other hand, the decentralized collector faces investment costs for the collection points, which influence the network density. An increasing weight of the travel effort requires a higher network density, which, again, increases the investment costs for collection points. Obviously, this effect is higher when the fixed costs for collection points are higher.

The variation in the discounting of the payment η in Figure 2.2 reveals a strong impact on the profit, in line with Equation (2.14) in Section 2.4.3. As a result, it is recommendable for a centralized collector to reduce the payment effect as much as possible, which can be achieved by fast processing of the used goods. Nevertheless, full elimination is impossible, due to the necessary physical shipments.

We observe for the decentralized collector that a reduction in the fixed investment costs enables a higher network density at the same costs, which increases the profit. Furthermore, it is recommendable to reduce the travel effort by selecting locations for the collection points that are easily reachable for the product holders. This “smart” placement can be observed in the actual case of ecoATMs, as most stations are located in easily accessible shopping malls (<http://www.ecoatm.com/find-a-location.html>).

We see a similar impact of the key problem parameters on the collected quantities in both collection systems (see the right side of Figure 2.2). Only if there is no discounted payment effect ($\eta = 1$) does the centralized collector collect more used products over the whole range of k . Otherwise, especially for low values of k , the decentralized collector acquires larger quantities. This property has been already explored analytically in Section 2.4.2 in Equation (2.9), as the network density effect is lower for small values of k and the discounted payment effect occurs only in the case when $\eta < 1$.

Interestingly, when linking the profits with the total collected products from Figure 2.2, we observe that the centralized collector may achieve lower profits than the decentralized collector even though the total number of collected products is higher (e.g. for $\eta = 1$). This can be explained by the difference in the quality ratio of the collected products (see Section 2.4.2 Equation (2.10)), which is illustrated in Figure 2.3. This figure shows the cumulated collected amounts per quality (q_1 =best,..., q_6 =worst) for the centralized collection system with $\eta = 1$ on the left side and for the decentralized collector with $F = 50000$ on the right side. It is easy to see that the centralized collector collects

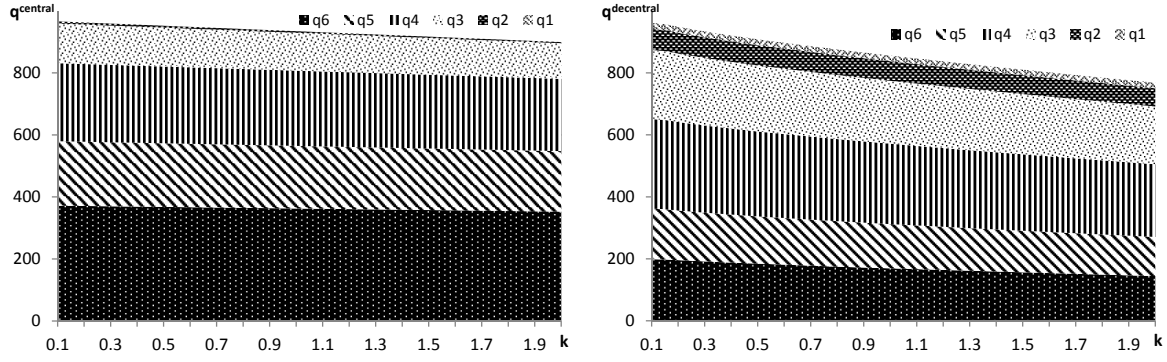


Figure 2.3: Acquired amounts per quality class for the centralized (left) and the decentralized system (right)

higher amounts of the poorer qualities in comparison with the decentralized collector. This effect is confirmed by current industry data. The reuse rate of all collected mobile phones in the USA is 65% and in the UK is over 50% (Geyer and Doctori Blass, 2010), whereas a decentralized collector like ecoATM finds a second life for about 75% of the used devices (Freeman, 2012).

2.5.3 Impact of product homogeneity on profitability

In the following section, we focus on the impact of product homogeneity on the profitability of both collection systems. We limit the analysis to the basic parameter case ($F = 50000, \eta = 0.9$). First, we show the influence of the number of quality classes on the profits of a decentralized and a centralized collector. Thus, we focus on the homogeneity of all the product attributes. Second, we compare the impact of the magnitude of the remanufacturing cost differences between classes on the profitability of both collection systems.

To analyse the influence of the number of quality classes, we combine the classes of our base case. $A1$ denotes the base case, containing six quality classes. In Scenario $A2$ we combine two quality classes, in Scenario $A3$ three quality classes, and in Scenario $A6$ all six classes. Thus, Scenario $A6$ represents the highest level of product homogeneity and Scenario $A1$ the lowest. In order to maintain the underlying profitability structure of the original data, we combine the quality classes weighted with their market size. For example, for the remanufacturing costs of the aggregated class $i = 12$, we obtain $r_{12} := (c_1 r_1 + c_2 r_2) / (c_1 + c_2)$. The resulting parameters for the combination of two (Scenario $A2$), three ($A3$), and six quality classes ($A6$) are shown in Table 2.3. The

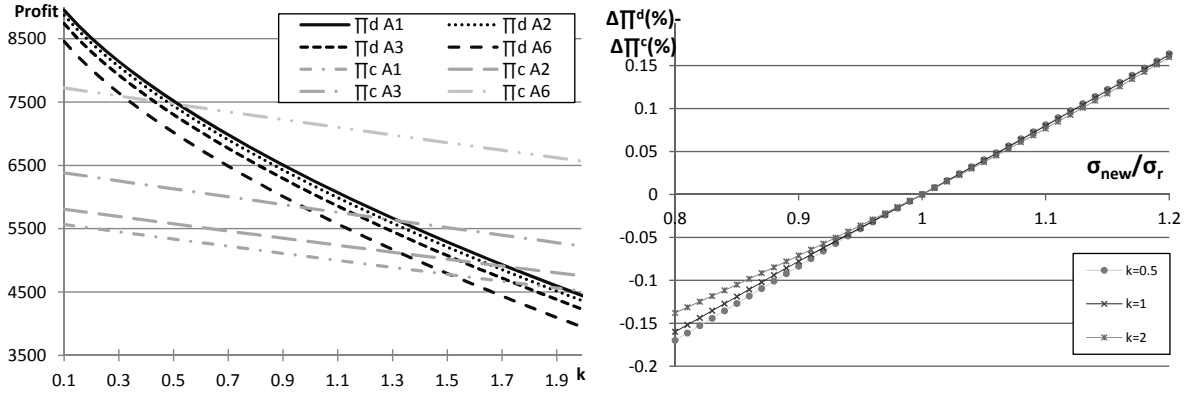


Figure 2.4: Impact of product homogeneity on profitability

basic data for Scenario A1 can be found in Table 2.2.

Scenario	A2			A3		A6
Quality class i	12	34	56	123	456	123456
Remanufacturing cost r_i	17.5	33	43	27.1	40	36.8
Intercept return function L_i	13.6	6.8	2.8	9.3	4	5.3
Slope return function ϕ_i/U_i	6	50	50	26	80	106

Table 2.3: Combination of quality classes

Figure 2.4 shows, on the left side, the optimal profits for the decentralized (Π^d) and the centralized collector (Π^c) for each scenario. We see that the profit of the decentralized collector is nearly stable across the scenario and decreases only a little with increasing product homogeneity. Thus, the weighted combination indeed preserves most of the original profitability of the data set. For the central collector, we see that the optimal profit decreases from A6 to A1. Thus, the centralized collector suffers with increasing product heterogeneity. The single acquisition price undervalues high quality and overvalues low quality, resulting in the skewed quality mix illustrated in Figure 2.3. Another interesting insight is that the relative profit difference between two scenarios decreases for an increasing number of quality classes. The profit loss between A6 and A3 is for example more than 20%, whereas the loss between A3 and A2 is less than 10%. Thus, we can say that the profit loss from an additional quality class is declining.

For the analysis of the homogeneity of the remanufacturing costs, we adjust the data set by changing the difference in the remanufacturing costs for each quality class relative to their mean ($\mu_r = 29.1\bar{6}$). This results in an even scaling of the original standard deviation ($\sigma_r = 14.634$) and makes it possible to increase or decrease the homogeneity

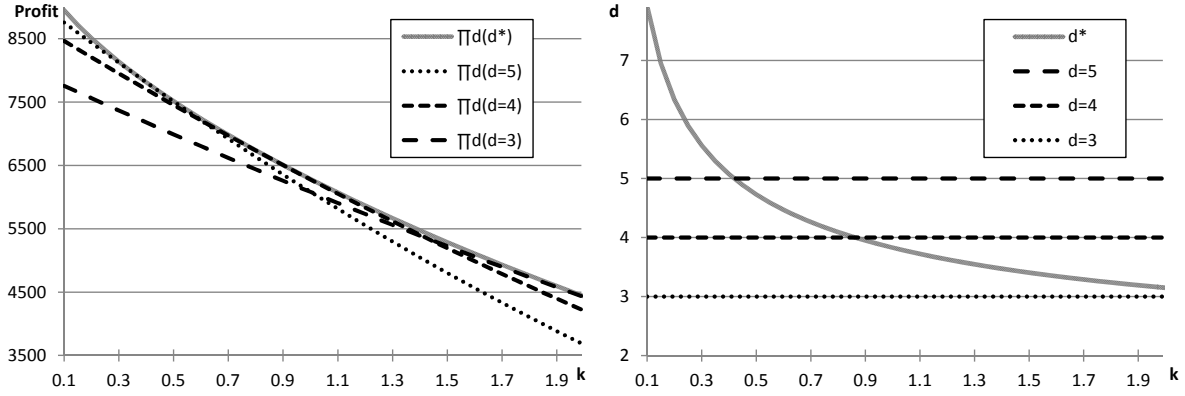


Figure 2.5: Fixed and optimal network density for the decentralized collector (right) and the corresponding influence on the optimized profit (left)

of the remanufacturing costs. The right side of Figure 2.4 illustrates the effect of higher ($\sigma_{new}/\sigma_r < 1$) or lower homogeneity ($\sigma_{new}/\sigma_r > 1$) on the relative profitability difference⁶ of the centralized and decentralized collectors for three different values of k (0.5, 1, 2). As we show the relative profit change, all the curves intersect the x -axis at $\sigma_{new}/\sigma_r = 1$. We observe that for higher homogeneity the profit of a decentralized collector decreases in comparison with a centralized collector, whereas for lower homogeneity ($\sigma_{new}/\sigma_r > 1$) it increases. We do not observe a major impact of the parameter k on this result. In total, we see a similar impact of the homogeneity of one product attribute as in the case of total product homogeneity. Again, increasing heterogeneity worsens the profitability of the centralized collector relative to the decentralized collector.

2.5.4 Fixed network density vs. optimal network density

We conclude our numerical study with a short illustration of the profit loss due to using a fixed network density instead of the optimal density (d^*). The left part of Figure 2.5 shows the profit of a decentralized collector for the optimal network density (d^*) and for three different fixed network densities ($d = 3, 4, 5$). The fixed and optimal network densities are illustrated on the right side of the same figure.

We observe that the optimal network density is always higher than the fixed network density of the centralized collector ($\tilde{d} = 1$). Thus, the decentralized collector always has fewer collection points than the centralized collector. Furthermore, we see that the profit function for a fixed network density (e.g. $\Pi^d(d = 5)$) is tangent to the profit function

⁶Due to the fact that the scaling of the standard deviation changes the original profitability of the data set, we illustrate here the relative profit change for the centralized and decentralized collectors.

for the optimal network density ($\Pi^d(d^*)$) at the point at which d is equal to d^* . We observe that the profit loss due to a fixed network density is very low for a wide range of k . For $k \in [0.7; 1.1]$ the profit difference between using a fixed network density of $d = 4$ and using the optimal network density is below 0.2%, while for $k \in [0.1; 2.0]$ it is below 6%. This means that the profit of the decentralized collector is fairly robust when the network density deviates moderately from optimality.

This result is consistent with the research literature. Fleischmann et al. (2003) illustrate the general robustness of a reverse logistics network for different return ratios. In our setting, the robustness in d can be explained by the substitutability of the higher or lower travel effort with higher or lower acquisition prices. This result has important practical implications for the decentralized collector. It shows that after the collection network is installed, it does not need to be adjusted immediately if the problem parameters change.

2.6 Conclusions

Our research is motivated by the practical observation of two different acquisition strategies for the remanufacturing of small electronic devices. We used a continuous approximation model to capture their different properties and analysed the interplay of APD and the costs of the underlying network design. After having determined the optimal acquisition price(s) and their respective collection quantities in a centralized and a decentralized collection system, we observed that the major benefit of a decentralized collection system is its better quality ratio of the collected products. We revealed that the value of acquisition price differentiation in a reverse logistics collection system has a structure analogous to the value of classical third-degree price discrimination. Thus, the same positive effects of classical price discrimination improve the profitability of a decentralized collector. Furthermore, we showed that other effects are driven by the delayed product holder payment and by the difference in the network density of both collection systems.

With the help of a data set from the mobile phone remanufacturing industry, we illustrated the influence of the key problem parameters on the profitability and the collected quantities of both collection systems. We extended the illustration for a product range to achieve general results and concluded that decentralized collection systems are especially recommendable for smaller electronic devices. In addition, we illustrated the

impact of product homogeneity on the relative performance of both collection systems. We observed again the analogy to classical price discrimination. As the value of classical price discrimination increases with greater heterogeneity of the market segments, in our reverse logistics setting, the decentralized collector benefits in the case of higher quality heterogeneity of the used products.

To conclude, our main literature contribution is the identification of APD as a driver for decentralizing the grading activities in a collection system, especially when collecting products with high quality uncertainties. Thus, besides a high marginal value of time (Guide et al., 2006) and reduced transportation costs of the used products (Tagaras and Zikopoulos, 2008), we introduce the exploitation of quality differences in the pricing decision as a third driver of decentralized grading systems. Furthermore, we have shown the analogy of a quality-dependent acquisition pricing strategy to classical third-degree price discrimination.

From a practical perspective, our results show that a decentralized collection system is in general better when collecting used products that are highly heterogeneous in their quality, resulting in large differences in remanufacturing costs and in the quality perception of the product holders. Furthermore, a decentralized collection system is better for used products that are not too bulky. Thus, the collected product categories of the ecoATMs, like used mobile phones or MP3 players are consistent with our results. Furthermore, our results show the profit loss of the centralized collectors due to their aggregated pricing strategy when the heterogeneity of the quality of the used product is high. Interestingly, we notice that some smaller centralized collectors are currently increasing the level of their upfront quality differentiation, which is performed by the product holder (www.wirkaufens.de). These collection systems are still limited in their degree of differentiation, due to the restricted technical skills of the product holders to achieve a perfect quality grading. Nevertheless, by increasing the quality levels, they can reduce the identified profit loss of their aggregated pricing strategy.

However, conversations with managers in charge of the product recovery have shown us that this detailed product holder upfront grading leads to new problems. One of these issues is the management of the conflicts arising between the product holders and the collector due to the contrary incentives when grading the used goods. A product holder has an incentive to grade the used product as better than it is because of the higher achievable acquisition price, whereas the collector has an incentive to downgrade the product. Additionally, we see the investigation of imperfect grading as an interesting

field for future research. Furthermore, we see a need to examine the product holder's perception of travel effort empirically as corresponding research literature regarding small electronic devices is scarce. Especially due to its impact on the profitability of different collection systems, we think that this is an important issue.

Chapter 3

Strategic Grading in the Acquisition Process

with Moritz Fleischmann¹

Abstract

Most recommerce providers have moved to a quality-dependent process for the acquisition of used products. They acquire the products via websites at which product holders have to give upfront quality statements and will be offered quality-dependent acquisition prices for their used devices.

Motivated by this development in the practice of reverse logistics, the aim of this paper is to analyse the product assessment process of a recommerce provider in detail. To this end, we propose a basic model with complete information which captures the individual behaviour of the recommerce provider and the product holder when assessing the used products in a sequential bargaining game. Using this basic model, we determine the optimal strategy of the product holder and recommerce provider. We find that the resulting strategy leads to an efficient allocation, although the recommerce provider can absorb the most bargaining potential due to its last mover advantage in the sequential

¹The research presented in this chapter is based on the paper “Strategic Grading in the Acquisition Process of a Reverse Supply Chain”, coauthored with Moritz Fleischmann.

game.

We then relax the assumption of complete information and include uncertainty about the residual value of the product holder. We show the trade-off for the optimal counteroffer decision and analyse the optimal strategy, using a logistic regression approach on a real-life data set of nearly 60,000 product submissions. The results reveal significant benefits of an optimal counteroffer decision in comparison with the currently applied strategy of the recommerce provider.

3.1 Introduction

Since the quality of a used product plays a major role in most reverse logistic environments, there are economic benefits which can be obtained by applying quality-dependent pricing strategies (Guide et al., 2003; Hahler and Fleischmann, 2013). The present paper analyses the quality assessment strategies of a recommerce provider who offers quality-dependent acquisition prices via websites to potential holders of used products. Our focus is on the individual strategic behaviour of the two players in the acquisition process when deciding upon the quality assessment.

Current practice shows a new trend in the acquisition of small electronic devices, such as mobile phones and MP3 players (see, for example, www.wirkaufens.de and www.rebuy.de). These so-called recommerce providers operate websites where they offer quality-dependent acquisition prices for used electronic devices. On their portals, an owner of a used good can select the specific model he or she wants to sell, as well as the specific condition of the good, and is then offered a provisional price. After accepting the offer, the good is sent by mail to the recommerce provider. When the good arrives, it is tested and compared with the product holder's description. The recommerce provider can then accept the used product and transfer the money to the product holder at this stage. However, he also has the option to update the offered acquisition price due to a misfit between the final grading result and the product holder's upfront grading. In that case, the product holder is offered a new, possible lower, acquisition price. If the product holder does not accept the new offer, the product is sent back.

Actual observations of product submissions to a recommerce provider reveal that there is a significant misfit in the quality stated by the product holder and the result of the grading by the recommerce provider. A representative data set shows that the considered recommerce provider has updated the provisional acquisition price for nearly 10% of the

submissions. As a counteroffer can on the one hand result in a complete loss of the submission, with significant costs involved, or on the other hand increase the profit achievable by the used product, it is a challenging task for a recommerce provider to decide on an update of the acquisition price.

In this paper, we analyse the specific behaviour of a recommerce provider and a product holder during the acquisition process. Our main interest is to identify the product assessment strategy which optimizes the recommerce provider's achievable profit from a product submission. Thus, our explicit research question is: How should a recommerce provider act optimally in the acquisition process of individual product returns and which factors drive his decisions? Additionally, we consider how structural changes in the acquisition process influence the behaviour of both players.

As the first step, we develop a sequential bargaining model with complete information which describes the acquisition process in detail. Using backward induction, we determine the optimal assessment strategies of the product holder and the recommerce provider. The influence on the optimal strategy of levers like shifting transportation costs and bonus payments to the product holder for correct quality assessments of the two players are shown. Furthermore, we extend our basic model approach by relaxing the assumption of complete information about the residual value of the holder of the used product and analyse the trade-off of the recommerce provider when deciding on the counteroffer option. A data set consisting of nearly 60,000 product acquisitions of a recommerce provider is used to approximate the product holder's behaviour with a logistic regression approach. By comparing the benefits of an optimal counteroffer decision with the applied strategy of the recommerce provider, we find valuable improvements affecting the profitability of the recommerce provider's acquisition process.

To summarize, our paper makes the following contributions:

- We propose a modeling framework which describes the acquisition process of a recommerce provider and identify the optimal strategy of the product holder and a recommerce provider concerning the assessment of the used products. The equilibrium reveals that the recommerce provider and the product holder have no incentive to properly assess the quality of the used product.
- Using this basic model, we analyse how levers like shifting transportation costs towards the product holder or an additional payment for a correct quality statement affect the behaviour of the two players.

- We add uncertainty about the residual value of the product holder to our basic model approach and show the resulting trade-offs in the counteroffer decision of the recommerce provider.
- A data set consisting of nearly 60,000 product acquisitions of a recommerce provider is used for an empirical analysis of the product holder's behaviour. An optimal counteroffer decision of the recommerce provider is derived using a logistic regression approach, in which the behaviour of the product holder is dependent on the relative price decrease of the counteroffer.
- A numerical comparison of the optimal counteroffer decision with the currently applied strategy illustrates the economic benefits of our developed approach. Furthermore, we find other managerial implications that improve the acquisition pricing strategy of a recommerce provider.

The remainder of this paper is organized as follows. Section 3.2 introduces the business of *FLIP4NEW* - a recommerce provider operating in Europe - which motivates our research. In Section 3.3, we position our work within the research literature. Then we introduce our basic model with its key assumptions in Section 3.4. Section 3.5 contains the analytical results derived from our model. In Section 3.6, we extend our basic model approach by introducing uncertainty about the product holder's residual valuation of the used product and explain our empirical estimation of the product holder's behaviour. The subsequent numerical illustration assesses our developed approach with the current practice of the recommerce provider. Section 3.7 summarizes our main contributions and gives directions for future research. All proofs are given in the Appendix.

3.2 Reverse logistics at a recommerce provider²

Main facts and history

FLIP4NEW offers its recommerce services to individual end consumers. The business started with the launch of the website www.flip4new.de in October 2009 and has become an integral part of the German recommerce market. At present, *FLIP4NEW* operates

²The case description of *FLIP4NEW* is based on a master thesis which was written at the Chair of Logistics and Supply Chain Management at the University of Mannheim (Taube, 2013). We have anonymised the original name of the company for the publication.

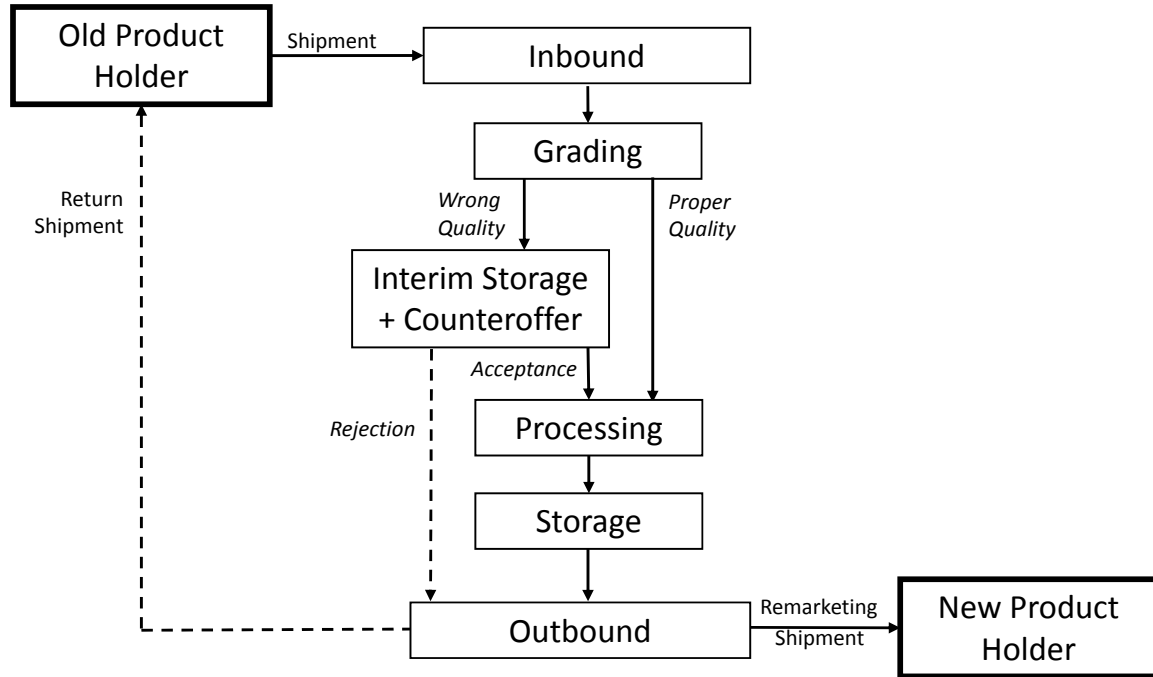


Figure 3.1: A typical product flow at a recommerce provider like *FLIP4NEW*

in Germany and Austria. The focus of *FLIP4NEW*'s operations was initially on the acquisition of *Apple* products. Today, the company repurchases a variety of used electronic goods from end consumers, ranging from used mobile phones to cameras or notebooks of different manufacturers.

Business model

FLIP4NEW acts as a broker in the second hand market. The company acquires used products from individual product holders and resells them via different channels to new individual consumers. In particular, the organisation of the return logistics and the offering of fixed prices are the main advantages for the product holders of using the services of a recommerce provider in comparison with, e.g., a self-executed direct sale to a new product holder via eBay. Other recommerce providers operating in Germany with a similar business model are, e.g., *wirkaufens* (www.wirkaufens.de) and *reBuy* (www.rebuy.de). In the following, we will take a closer look at the flow of a handed-in product at *FLIP4NEW*, which is illustrated in Figure 3.1 and is typical for the current practice in the recommerce business.

First, the product holder has to grade the product via pre-defined quality criteria, which can be found on *FLIP4NEW*'s website. These quality criteria are dependent on the product category and include, e.g., the optical condition, the functionality, and the accessories included. After stating these quality features via the website, a provisional acquisition price is determined and offered. Afterwards, the product holder decides whether to hand in the product and send it via mail to *FLIP4NEW*. The shipment is free of charge for the product holder. After the product has arrived at *FLIP4NEW*'s site (Inbound), the quality of the product is checked and the actual quality of the product is determined (Grading). If the quality of the product was assessed correctly by the product holder (Proper Quality), the product is acquired by *FLIP4NEW* at the provisional acquisition price. Dependent on the product category and the specific quality of the product, *FLIP4NEW* executes process steps, such as, e.g., cleaning and deletion of personal data on the product (Processing). Afterwards, the product moves into the storage area (Storage). However, if the estimated quality of the product deviates from the actual quality of the good (Wrong Quality), *FLIP4NEW* has to decide about offering an adjusted counteroffer or buying the product for the inappropriate price. In case of a counteroffer, the product holder receives a new purchasing offer from *FLIP4NEW* via email. During the time that *FLIP4NEW* is waiting for the response on the counteroffer, the used product is stored in an interim storage area. If the product holder accepts the new offer, the product is acquired by the company and moves via a processing step into the storage area. In case of a rejection of the new price offer by the product holder, *FLIP4NEW* sends the product back to the holder (Outbound). In doing so, *FLIP4NEW* bears all the costs of transportation.

For the stored and acquired used products, *FLIP4NEW* starts the remarketing directly. An important redistribution channel to the consumer market is the 'buy it now'-option of its cooperating partner *eBay*. Most of the acquired products are sold via this channel. For this remarketing channel, *FLIP4NEW* generates a separate offer for every product with photos and a detailed description of its quality. When the used product has been resold, *FLIP4NEW* ships the product to the new product holder.

Main profit levers

The general business process of a reverse supply chain has been classified into three main areas in the research literature (Guide and Jayaraman, 2000; Guide and Wassenhove, 2009):

- Remanufactured products market development (back end)
- Remanufacturing operational issues (engine)
- Product returns management (front end)

Using this process classification, we describe in the following the main levers which drive the profitability of a recommerce provider.

The first main lever is the connection to strong remarketing channels. Here, one key property of *FLIP4NEW*'s strategy is to sell the used products with a one-year warranty. This leads to a higher trust in the quality of the used products and is the reason why *FLIP4NEW* can obtain high reselling prices on the secondary markets. Subramanian and Subramanyam (2012) and Guide and Li (2010) are current research papers which consider the sales of used products on *eBay*.

Considering the engine of a recommerce provider, it is important to have quick, reliable, and cost-efficient processes in the return completion. Especially, when it is the case that a returned product depreciates quickly, e.g., due to innovations or product upgrades (e.g., mobile phones or tablets), then quick inbound, grading, and remarketing processes are crucial (Guide et al., 2006; Galbreth et al., 2013). Reliability is particularly important in the grading process, as the used products can have hidden defects (e.g., water damage or unwanted switch-off behaviour). If the recommerce provider does not discover these defects, he will pay the wrong acquisition price and will resell a non-functional product which probably results in warranty issues. In addition, the processes have to be efficient as margins are low in the recommerce business and profit is generated by handling a great many handed-in products. For this reason, *FLIP4NEW* carries out only simple refurbishing activities. Advanced technical processing like repairing or product upgrading is done only in exceptional cases.

Regarding the front end of a recommerce provider, we identify the acquisition pricing strategy as another main lever for profitability. Depending on the exact pricing for the used products, a recommerce provider can initiate product returns and thus steer the return volumes. *FLIP4NEW* uses a rather new strategy, in which the product holders carry out an upfront quality grading of the used products. As a result, *FLIP4NEW* already gains information about the quality of the product before it arrives at its facilities. Furthermore, *FLIP4NEW* is able to differentiate the acquisition price according to the quality of the product. Some of the benefits of this pricing strategy have already been analysed for different reverse logistics settings (Guide et al., 2003; Hahler

and Fleischmann, 2013).

Our paper is mainly focussed on the front end of the acquisition process and especially on the managerial challenges arising from the upfront quality grading process for a recommerce provider like *FLIP4NEW*. One major issue is the decision about the acceptance or rejection of the returned products, with regard to the quality statements by the product holders. On the one hand, a counteroffer can result in a complete loss of the submission with significant costs involved for the recommerce provider. On the other hand, the counteroffer gives the recommerce provider a possibility for negotiation, which probably allows increasing the achievable profit of a product submission. Thus, it is a challenging task for a recommerce provider to decide on an update of the acquisition price.

FLIP4NEW currently manages this decision by offering a counteroffer based on the relative difference between the price for the true quality and the stated quality. If this difference is higher than a certain threshold, it will make a counteroffer. Otherwise, *FLIP4NEW* accepts the stated quality classification and pays the original acquisition price.

However, an analysis of a data set of product submissions reveals the high relevance of this issue for *FLIP4NEW*. The data set shows that *FLIP4NEW* offers updated acquisition prices for nearly 10% of the handed-in products. Reconsidering the background of the above described generous acceptance rule for the counteroffer decision, this counteroffer rate is even more significant.

The goal of this paper is to investigate the decisions of a recommerce provider like *FLIP4NEW* and the product holder in the acquisition process. The product holder owns a single used product and has to decide on submitting it at the beginning of the process. In case of submission of the product, a specific quality statement for the used product has to be decided on, which will determine the resulting provisional acquisition price. A submitted product will be tested by the recommerce provider and the recommerce provider has to decide about accepting the provisional acquisition price or offering a new price for the used product. When the recommerce provider chooses the counteroffer option, he has to declare to what level the product is devalued. The product holder then decides on the acceptance or rejection of the new offer at the end of the acquisition process. To summarize, we consider the product holder's decision about the initial product submission, the quality selection, and the acceptance of a possible counteroffer. The considered decisions of the recommerce provider are the acceptance of the provisional

acquisition price, and the optional counteroffer in the case of a rejection.

3.3 Literature

Souza (2013) gives a broad and recent review of the field of closed-loop supply chains and provides further research opportunities. He emphasizes the need for practice-driven empirical research, especially on the acquisition and collection process, and on consumer behaviour in this field. The same recommendations for future approaches are given by Guide and Wassenhove (2009). They mention the difficulty and time effort of working with the industry, but also highlight the potential rewards.

The problem setting considered here concerns two main processes of a reverse supply chain—acquisition and grading. Several issues in reverse logistics with a strong focus on these two processes have already been analysed. We refer to Fleischmann et al. (2010) for a broad overview. In the following, we introduce the most relevant and related research papers which concern the acquisition and grading process in reverse logistics. We begin with the literature stream about the acquisition process.

The research field of a profit-oriented acquisition management has been opened by Guide and Jayaraman (2000), and Guide and Wassenhove (2001). Prior to that, the managerial perspective in the reverse logistics field was mostly cost-oriented and assumed a passive return process without any offered incentives for the used products. Furthermore, Guide et al. (2003) introduced quality dependent acquisition prices which enable the control of the quantity and quality of the returned products. Other important papers following their approach include Ray et al. (2005), who consider a continuous quality differentiation instead of using discrete quality classes, and Karakayali et al. (2007), who consider different reverse channel structures of an OEM and determine optimal acquisition prices for remanufactured parts. Our work is strongly related to this research stream as we consider a profit-oriented recommerce provider who offers quality dependent prices for used products to individual product holders. Nevertheless, our focus is not on the pricing decision itself. We consider the strategic quality statements during the acquisition process of the recommerce provider and the product holder. These quality statements of both players result indirectly in the final acquisition price.

We adopt the classification of Fleischmann et al. (2010) for the research literature about the grading process. They divide this field into two streams. The first stream considers the value of the grading information in the subsequent processing of the re-

turned products. Souza et al. (2002) and Ketzenberg et al. (2003) were the first to consider the grading process in this context. Ketzenberg et al. (2003) find that the availability of the grading information about the remanufacturing parts generally improves flow times in the remanufacturing system. Similar studies analysing the value of the grading information by comparing a remanufacturing system with and without an upfront grading process include Guide et al. (2005), Aras et al. (2004), and Zikopoulos and Tagaras (2008). The focus of our work is not on the value of the grading information for the operational performance of the remanufacturing system. In our setting, the holder of the used product carries out an upfront quality grading. This grading information is used by the recommerce provider for a strategic product assessment. Thus, we contribute to this stream as we consider how the upfront quality grading influences the acquisition process.

The second literature stream on grading compares multiple options for the grading process. Two important studies in this stream which are strongly related to our work are Guide et al. (2006) and Blackburn et al. (2004). They evaluate different grading locations in the return process. One major result is that a less time-consuming decentralized grading set-up can be more beneficial than a cost-efficient slower one, especially for used products with a high marginal value of time. These high marginal values of time are common, e.g., for most returns in the electronic goods industry. In our problem setting, the focus of a recommerce provider is on electronic goods from end consumers. Thus, we also incorporate the time value loss in our analysis of the acquisition process and observe its impact on the grading strategy of the recommerce provider and the product holder. Additionally, we contribute to this stream by analysing different payment structures in the acquisition process and show the impact of these levers on the outcome of the acquisition process.

However, to our knowledge, there is nothing in the literature which takes into account the upfront quality grading in the above described acquisition process in the recommerce business and which analyses the resulting strategic interaction between the recommerce provider and the a product holder. Our aim is to fill this research gap, which has been identified by Hahler and Fleischmann (2013). By doing so, we contribute to the literature as we identify the counteroffer decision in the acquisition process of a recommerce provider as a new business decision in the field of reverse logistics. Furthermore, our work brings together the research streams about the acquisition and grading process as we address these processes jointly. Additionally, a close collaboration with a

recommerce provider during this project yielded new insights into this fast developing industry. Thus, our research approach addresses the needs identified by Souza (2013) and Guide and Wassenhove (2009) as we consider a novel practice-driven problem setting and provide empirical results from an actual data set from the recommerce industry.

There are two recent research papers which are related to our problem setting. The first one is the aforementioned work by Hahler and Fleischmann (2013). They compare two collection system configurations from the reverse logistics industry. One is a decentralised system in which the grading is done close to the product holder, whereas the other system has a centralised grading process. As a centralised collector has almost the same business model as a recommerce provider, most of the results concerning the network design of a collection system and their respective grading strategy can be adapted for the above mentioned business case of *FLIP4NEW*. Nevertheless, our focus in this paper is on the strategic interaction between the two players involved during the acquisition process. This interaction is not included in the analysis of Hahler and Fleischmann (2013).

The second closely related research paper is Gönsch (2014). He compares two acquisition pricing strategies. In the first strategy, the manufacturer offers fixed prices to the product holders for handing in their used products. In the second strategy, the collector bargains with the product holder. Furthermore, Gönsch (2014) shows how competition from a third-party remanufacturer influences the results compared with a monopolistic setting. The main difference from our work is that Gönsch (2014) considers only one time period, and thus does not focus on the negotiation process itself. He divides the total surplus of the product submission by a factor describing the relative bargaining power of each player. The aim of our work is to analyse the business decisions of a recommerce provider in the acquisition process from a practice perspective. We develop a sequential game for capturing the corresponding interactions in detail.

3.4 Basic model

As described in Section 3.2, we consider a single product submission of an individual product holder to a recommerce provider and analyse the decisions of both players during the acquisition process. We model this setting as a sequential game. The product holder decides on submitting his used product for a specific price and is faced with a possible counteroffer at the end of the game. The recommerce provider either accepts

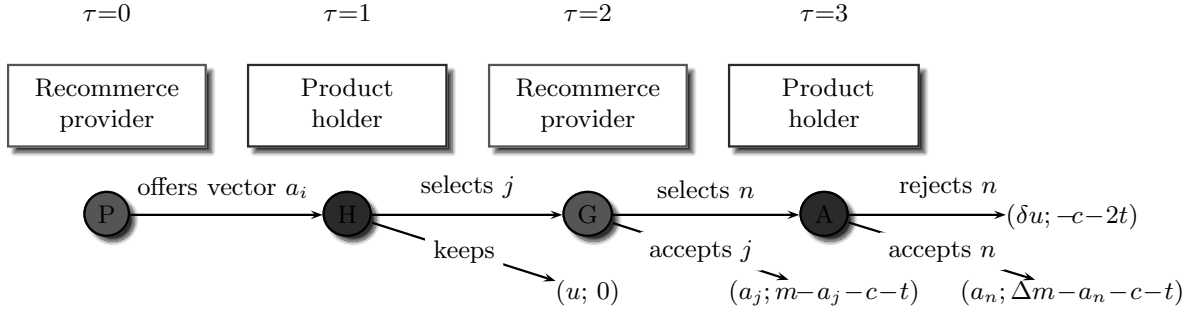


Figure 3.2: Acquisition process of a recommerce provider

Symbol	Description
\mathcal{I}	Set of quality levels $\mathcal{I} = \{1, \dots, I\}$
a_i	Acquisition price for product of quality i
u	Product holder's residual value for the used product
m	Margin for the considered product submission
c	Grading costs (independent of quality i)
t	Product shipment costs
Δ	Multiplier for the marginal loss due to a longer acquisition process
δ	Multiplier for the loss in product holder's residual value

Table 3.1: Notation

the provisional acquisition price or offers a new price for the used product. The interaction during the acquisition process is shown in Figure 3.2. The illustrated sequential game indicates the moves of the recommerce provider and the product holder. The corresponding payoffs for the product holder and the recommerce provider are listed in brackets at the four possible endpoints of the game.

In the following, we present our model assumptions and provide a short discussion. Then, we describe the single steps of the game in detail. The notation used is summarized in Table 3.1.

Assumptions

1. Assumption: *The recommerce provider distinguishes between I different quality classes and offers a vector of quality-dependent acquisition prices a_i for $i \in \mathcal{I}$.*

The recommerce provider specifies the single quality classes i and the corresponding prices a_i with $i \in \mathcal{I}$. The pricing flexibility of the recommerce provider is strongly limited as the recommerce provider has to set the prices in a competitive environment

and the quality differentiation level is restricted for reasons of customer usability. Thus, we assume that the prices and quality classes are exogenous in the sequential game and are not adjusted for an individual customer. In Section 3.6, we derive recommendations for defining the price differences between two quality classes based on the analysis of the practice data set.

2. Assumption: *The recommerce provider can achieve a reselling price for the considered product submission on the secondary market which determines the achievable margin m .*

As in Hahler and Fleischmann (2013), we focus on the purchase of used products by the recommerce provider and assume the market price to be fixed for a specific output quality i . Consequently, the recommerce provider is a price taker on the resale market. We consider a margin (m) which is the market price reduced by the costs which occur for every product when it is resold. These costs are, e.g., the processing costs for cleaning and data deletion, costs for remarketing, and shipment costs. Thus, the disposition decision of the recommerce provider is defined exogenously by the specific quality class of the used product.

3. Assumption: *The recommerce provider incurs grading costs c and shipment costs t .*

The process for determining the true quality of the used product results in costs c which are independent of the quality. For the shipment of the used product from the product holder to the site of the recommerce provider, the recommerce provider pays transportation costs t . In the base case, we assume additionally that the recommerce provider pays the return shipment costs of the product in case the product holder does not accept a given counteroffer.

4. Assumption: *We consider an individual product holder who decides about using the service of the recommerce provider. This product holder attributes a residual value u to the product.*

Because the used product can still be used, e.g., as a replacement device, the used product has a residual value for the product holder.

5. Assumption: *If the acquisition process is delayed due to a counteroffer of the recommerce provider ($\tau = 3$), the achievable margin m in the payoff of the recommerce provider is discounted by Δ ($0 \leq \Delta \leq 1$). Analogously, the holder's residual value of the used product is discounted by δ ($0 \leq \delta \leq 1$).*

There are product submissions where the whole acquisition process takes four weeks

due to long response times for the counteroffers. As already noted in Section 3.2, the considered products lose value during that time period. This value loss is captured by the multiplier Δ .

We discount the product holder's residual value of the used product by δ because the product was not available for use during the transaction process. As described above, this can take up to four weeks. Furthermore, the product holder has an additional handling effort to get the product back.

6. Assumption: *In the sequential game, the product holder and the recommerce provider have complete information and behave rationally.*

In what follows, we will describe the acquisition process of the recommerce provider as a finite sequential game. We assume that each player has complete information. Thus, each player is aware of the rival's prior moves and knows the full history of the play of the game thus far. In Section 3.6, we relax the complete information assumption and introduce uncertainty about the product holder's residual value u .

Sequential game

$\tau = 0$: The recommerce provider announces I discrete quality classes and their corresponding acquisition prices a_i .

$\tau = 1$: The product holder assesses the quality of his used product and receives an offer via the website of the recommerce provider for the selected quality class (we use j to describe the selected quality class after the upfront quality grading of the product holder). At this point, the product holder makes an individual decision to hand in the product based on the offered acquisition price a_j . If the product holder accepts the offer of the recommerce provider, the product is sent to the recommerce provider. Otherwise, the product holder keeps the used product and the game terminates. In this case, the product holder still has the residual value u of the product. As the product holder can manipulate the offer in his or her favour, the price a_j offered in the first period can be regarded as an offer for sale by the product holder to the recommerce provider.

$\tau = 2$: The product quality will be determined by the recommerce provider after the shipment has arrived. The result of the grading process is denoted by r (true quality), which can be equal to the quality determined by the product holder, j , but does not have to be. At this point, the recommerce provider has to decide whether to accept the provisional acquisition price or to offer an adjusted one. If the recommerce provider accepts the handed-in used product for the stated quality, the product holder will get

the acquisition price a_j and the recommerce provider will achieve $m - a_j - c - t$. If the recommerce provider chooses to update the acquisition price, the product holder will receive a counteroffer for handing in the used product. We use n to describe the new offered quality, since the stated quality of the recommerce provider does not have to be equal to the true (graded) quality r .

$\tau = 3$: The end of the sequence is the decision by the product holder about the updated acquisition price a_n . At this stage, the product holder can accept the new offer, which results in payoffs of a_n to the product holder and $\Delta m - a_n - c - t$ to the recommerce provider. We do not discount the delayed payment of the acquisition price a_n as we assume that the cost of capital is negligible in comparison with the loss in value of the used product.

If the product holder rejects the new offer, the product will be sent back to the product holder. This results in payoffs of $-c - 2t$ for the recommerce provider because the recommerce provider has to pay the shipment costs t for returning the product. The payoff for the product holder is δu .

3.5 Analysis

We use the defined basic model to analyse the individual decisions of the product holder and the recommerce provider in the acquisition process. We use backward induction to determine each player's optimal strategy and find the equilibrium in the current grading process. Furthermore, we analyse the influence of two potential changes in the acquisition process on the optimal strategies of the two players.

3.5.1 Optimal bargaining strategies

Product holder's acceptance decision (Decision at $\tau = 3$)

We assume that the product holder has handed in the used product and has been offered an updated acquisition price a_n by the recommerce provider. At this moment, the product holder's decision is to accept or reject the counteroffer of the recommerce provider. A rational product holder will accept the counteroffer a_n if it is bigger than the discounted residual value ($a_n \geq \delta u$). Otherwise ($a_n < \delta u$), it is optimal for the product holder to reject the new offer.

Recommerce provider's acceptance and counteroffer decision (Decision at $\tau = 2$)

At $\tau = 2$, the recommerce provider decides whether to accept or reject the provisional acquisition price a_j . In case of rejection, he makes a counteroffer a_n to the product holder. As this decision consists of two steps, we begin with the selection of the optimal counteroffer a_n .

- 1) The optimal counteroffer a_n depends on the payoffs for the recommerce provider in the last step of the sequential game. The recommerce provider compares the payoff for a rejection of the counteroffer ($-c - 2t$) with the payoff in case of an acceptance ($\Delta m - a_n - c - t$). As the recommerce provider anticipates that the product holder will accept the counteroffer a_n if it is greater than or equal to the discounted residual value δu , he has to offer at least δu in case he wants the product holder to accept the new offer. Thus, we define $a_n(\delta u)$ as the smallest a_n which satisfies $a_n \geq \delta u$. Using this information, the optimal decision of the recommerce provider is $a_n(\delta u)$ if the following holds:

$$\begin{aligned} \Delta m - a_n(\delta u) - c - t &\geq -c - 2t \\ \Leftrightarrow a_n(\delta u) &\leq \Delta m + t. \end{aligned} \quad (3.1)$$

Otherwise, it is optimal to offer a price which is lower than the residual value. This counteroffer will be rejected by the product holder.

- 2) In a second step, the recommerce provider compares the payoff from the optimal counteroffer decision with the payoff from an immediate acceptance of a_j .
 - a) If the optimal counteroffer decision is $a_n(\delta u)$, the recommerce provider accepts a_j if the following holds:

$$\begin{aligned} m - a_j - c - t &\geq \Delta m - a_n(\delta u) - c - t \\ \Leftrightarrow (1 - \Delta)m &\geq a_j - a_n(\delta u). \end{aligned} \quad (3.2)$$

Linking Inequality (3.1) with (3.2) results in the following condition for this case:

$$a_j \leq a_n(\delta u) + (1 - \Delta)m \leq m + t. \quad (3.3)$$

- b) In case the optimal counteroffer is lower than the residual value (Inequality (3.1) is not satisfied), the recommerce provider accepts a_j if the following holds:

$$\begin{aligned} m - a_j - c - t &\geq -c - 2t \\ \Leftrightarrow m + t &\geq a_j. \end{aligned} \quad (3.4)$$

Linking again both conditions results in the following inequality for this case:

$$a_j \leq m + t \leq a_n(\delta u) + (1 - \Delta)m. \quad (3.5)$$

To sum up, the recommerce provider's optimal decision is to accept a_j if the following holds:

$$a_j \leq \min(a_n(\delta u) + (1 - \Delta)m, m + t). \quad (3.6)$$

Product holder's hand-in decision (Decision at $\tau = 1$)

The first decision of the product holder in the sequential game is whether to hand in or to keep the used product. In case the product holder decides to hand in the used product, a selection as to the stated quality j has to be made. Thus, the product holder can keep the product with its residual value u or can achieve one of the three other possible end points of the sequential game with their respective payoffs, depending on the specific quality selection. In the following, we consider the conditions that have to be fulfilled to obtain each of these payoffs:

1. a_j : As we have identified above, the recommerce provider will accept the provisional acquisition price a_j if it satisfies Inequality (3.6), i.e. $a_j \leq \min(a_n(\delta u) + (1 - \Delta)m, m + t)$.
2. $a_n(\delta u)$: The product holder can trigger the counteroffer $a_n(\delta u)$ if the selected quality j leads to a provisional acquisition price which satisfies $a_j > \min(a_n(\delta u) + (1 - \Delta)m, m + t)$ and $a_n(\delta u) + (1 - \Delta)m \leq m + t$.
3. δu : The product holder obtains the discounted residual value δu if the selected quality j leads to a provisional acquisition price which satisfies $a_j > \min(a_n(\delta u) + (1 - \Delta)m, m + t)$ and $a_n(\delta u) + (1 - \Delta)m > m + t$. The corresponding counteroffer

of the recommerce provider will be lower than the discounted residual value of the product holder, and thus the offer will be rejected.

4. u : The product holder obtains the residual value u on deciding to keep the product at the beginning of the sequential game.

We observe that the third end point (δu) is by definition lower than the residual value at the beginning of the game (u). Thus, it is never optimal for the product holder to reach this payoff. Furthermore, we assume in the following that the quality differentiation granularity of the recommerce provider is high enough so that the optimal counteroffer of the recommerce provider $a_n(\delta u)$ is always lower than the product holder's residual value u ($u \geq a_n(\delta u)$). This implies that the second payoff ($a_n(\delta u)$) is also not desirable for the product holder.

The first payoff a_j will obtain if the recommerce provider accepts the provisional acquisition price immediately. If there exists more than one provisional acquisition price a_j which fulfils this condition, then the product holder's optimal acquisition price a^* will be the highest one of these, i.e.

$$a^* = \max\{a_j | a_j \leq \min(a_n(\delta u) + (1 - \Delta)m, m + t)\}. \quad (3.7)$$

Consequently, the product holder's hand-in decision depends on comparing the highest achievable payoff for a return a^* with the residual value u . If the optimal provisional acquisition price a^* is higher than the residual value of the product u , the product holder will hand in the product, otherwise it will be kept. We add this property to Equation (3.7), which leads to the optimal provisional acquisition price a^* :

$$a^* = \max\{a_j | u \leq a_j \leq \min(a_n(\delta u) + (1 - \Delta)m, m + t)\}. \quad (3.8)$$

If this set is empty, it is optimal for the product holder to keep the used product.

Let us consider Equation (3.8) for the case that $a_n(\delta u) + (1 - \Delta)m > m + t$. Then handing in the product is optimal if the following two conditions are satisfied simultaneously:

$$\left. \begin{array}{l} m + t \geq u \\ \Delta m + t \leq a_n(\delta u) = \min\{a_n | a_n \geq \delta u\} \approx \delta u \end{array} \right\} \Rightarrow \begin{array}{l} m + t \geq u \\ \Delta m + t \leq \delta u. \end{array}$$

These conditions can only be satisfied simultaneously if the marginal loss over time of the used product (Δ) is much higher than the discounting of the residual value (δ), or if the quality differentiation granularity is very low. As these are not the case for our acquisition setting, we neglect this theoretical solution of the game in the following and focus on the case of Equation (3.8) in which $a_n(\delta u) + (1 - \Delta)m > m + t$. Thus, the optimal strategy of the product holder is to select the quality j with the highest a_j as follows:

$$a^* = \max\{a_j | u \leq a_j \leq a_n(\delta u) + (1 - \Delta)m\}. \quad (3.9)$$

If there is no quality class j which satisfies these conditions, the optimal strategy of the product holder is to keep the used product. In the following, we take a closer look at this equilibrium of the game.

3.5.2 Analysis of the equilibrium solution

When the used product is handed in, the optimal strategies of the product holder and the recommerce provider reveal an interesting equilibrium. The product holder will state the product quality j so as to receive the maximum acquisition price a^* which the recommerce provider is still willing to accept. The price a^* is limited as the recommerce provider has the advantage of the last offer in the acquisition process. Thus, he always has the possibility to downgrade the product and hence can minimize the acquisition price. In sequential finite games, this property is called the last mover advantage.

Rearranging the optimal quality selection of the product holder described in Equation (3.9) gives us the following:

$$\underbrace{a^* - a_n(\delta u)}_{\text{Additional gain by downgrading}} < \underbrace{(1 - \Delta)m}_{\text{Loss of market value}}. \quad (3.10)$$

Interestingly, we can interpret the recommerce provider's trade-off decision for the counteroffer from this inequality. The term on the left side describes his acquisition cost saving when he decides to downgrade the product. The term on the right side defines the value loss of the used product caused by prolonging the acquisition process. Thus, given the product holder's optimal strategy, the recommerce provider can devalue the product by no more than the loss in market value.

We can make two additional observations from Inequality (3.10). We denote the correct acquisition price by a_r , i.e. the price for the actual product quality r . Interestingly, Equation (3.9) is independent of a_r . Depending on the equilibrium solution for the optimal provisional acquisition price a^* , the correct acquisition price a_r can be higher or lower than a^* . If $a^* < a_r$, the equilibrium solution improves the outcome for the recommerce provider as he can reduce the acquisition price. If $a^* > a_r$, the product holder obtains a higher gain. Depending on the relation between a^* and a_r , Inequality (3.10) shows in which range the product holder or the recommerce provider can over- or underestimate the handed-in product. We call this observation the “incentive problem in quality grading” because the equilibrium solution reveals that there is no incentive for either player to make a correct quality statement.

Comparing the solution of the optimal strategies in the bargaining game with the other possible solutions reveals that the summed-up payoffs in the equilibrium are higher than in any other later outcome of the sequential game. This holds because the product faces a significant loss of market value over time. Furthermore, we observe by a comparison that no player can improve their payoff without reducing the payoff of the other player. Thus, the equilibrium solution is efficient (Fudenberg and Tirole, 1991).

The total potential profit in the game is $m - c - t - u$. A closer look at the profit allocation between the two players shows that the recommerce provider gains most of the profit in the game as he has the last mover advantage. The equilibrium shows that the product holder gains only $(1 - \Delta)m + a_n(\delta u) - u$ whereas the recommerce provider obtains $\Delta m - a_n(\delta u) - c - t$. Approximating $a_n(\delta u) \approx \delta u$ and $\Delta \approx \delta$, we can simplify the above allocation to $(1 - \Delta)(m - u)$ for the product holder and $\Delta(m - u) - c - t$ for the recommerce provider. Thus, the multiplier of the value loss over time (Δ) defines how the profit is shared between the two players. As, in general, $(1 - \Delta) \ll \Delta$ (and $(1 - \delta) \ll \delta$), the recommerce provider gains most of the potential profit. However, the recommerce provider must also bear the costs $(c + t)$. Inequality (3.10) explains this allocation. Due to the last mover advantage, the recommerce provider can reduce the product holder’s payoff at the end of the game to the user’s discounted residual value. Additionally, the product holder anticipates that the recommerce provider wants to avoid a payoff with a discounted margin in the last period of the game. Thus, the product holder can overstate the discounted residual value by at most the amount of the product’s time value loss $(1 - \Delta)$.

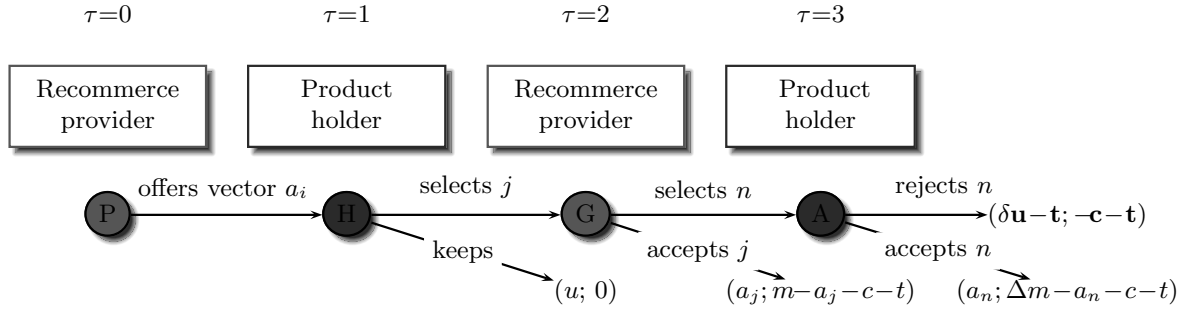


Figure 3.3: Acquisition process with a shift of the return shipment costs towards the product holder

3.5.3 Effect of levers on the equilibrium solution

Transportation cost shift towards product holder

In some respects, the new EU directive on consumer rights (European Commission, 2013) gives e-commerce providers more freedom for operating their businesses. Especially, regulations concerning the burden of the transportation costs have been relaxed. Motivated by this current situation, we consider in the following a structural change in the acquisition process and evaluate the effect on the optimal strategies in the sequential game. We shift the transportation cost t towards the product holder when rejecting the counteroffer of the recommerce provider. Figure 3.3 shows the acquisition process with the adjusted payoffs.

The following equation shows the new equilibrium solution when resolving the adjusted sequential game in Figure 3.3:

$$a^* = \max\{a_j | u \leq a_j \leq a_n(\delta u) - t + (1 - \Delta)m\} \quad (3.11)$$

We see that the discounted residual value of the product holder will be reduced by the shipment costs and, thus, the recommerce provider can obtain a higher gain by downgrading the product. As the product holder anticipates this behaviour when deciding to hand in the used product, the initial price offer (a_j) has to be reduced. Evaluating Equation (3.11) shows the new profit share of $(1 - \Delta)m + a_n(\delta u) - u - t$ for the product holder and $\Delta m - a_n(\delta u) - c$ for the recommerce provider. A comparison of the new profit allocation with the base case shows that the transportation costs t are shifted towards the product holder.

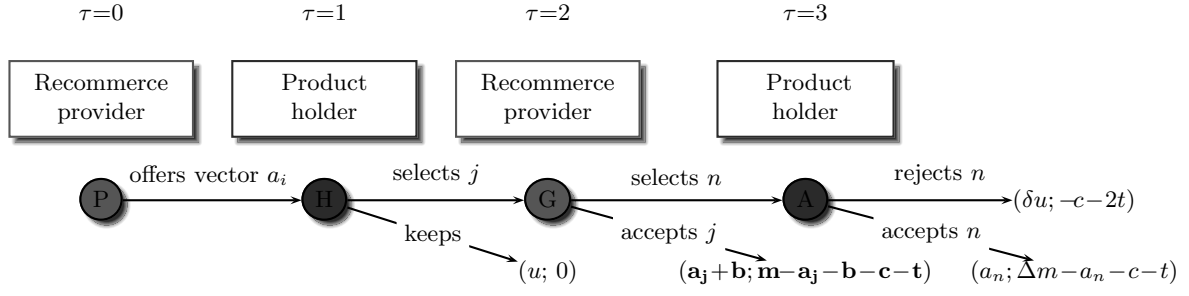


Figure 3.4: Acquisition process with bonus payments b for correct quality assessment

Bonus payment for correct quality assessment

Current product submissions to *FLIP4NEW* show that a significant number of product holders give wrong quality statements for their used products. Thus, we evaluate in the following a bonus payment b from the recommerce provider for the product holder in the case that the recommerce provider accepts the provisional acquisition price a_j directly. See Figure 3.4 for the illustration of the changes.

The additional bonus payment b is paid if the quality statement of the product holder has been accepted. The following equation shows the new equilibrium solution for the adjusted sequential game in Figure 3.4:

$$a^* = \max\{a_j | u \leq a_j \leq a_n(\delta u) - b + (1 - \Delta)m\} \quad (3.12)$$

As Equation (3.12) has the same structure as Equation (3.11), one might expect a similar effect of the bonus payment as that of the transportation cost shift. The additional acquisition cost reduction upon downgrading by the recommerce provider increases in relation to the loss of market value. The major difference between this lever and the above transportation cost shift is that the product holder receives the bonus payment b . Thus, reassessing the profit share reveals the same allocation as in the base case. The product holder still gains $(1 - \Delta)m + a_n(\delta u) - u$ and the recommerce provider $\Delta m - a_n(\delta u) - c - t$. This is why we can conclude that an additional bonus payment has no influence on the profit allocation of this solution of the game. This result can be explained by the fact that the equilibrium of an immediate offer acceptance by the recommerce provider has been already achieved in Section 3.5.1. The additional incentive of the bonus payment will be factored in by the product holder, and thus has no effect.

3.6 Incorporation of uncertainty about the product holder's residual value

A key factor which drives the results of the sequential game analysed in the previous section is the assumption of complete information. Specifically, the recommerce provider's knowledge of the exact product holder's residual value gives the recommerce provider the last mover advantage when making a counteroffer. We relax this assumption in the following and assess the resulting model empirically.

To this end, we extend our basic model and incorporate uncertainty about the residual value of the product holder. Then we introduce the used product and consumer data of *FLIP4NEW* and propose an approach for estimating the individual behaviour of the product holders. We assume that the counteroffer acceptance decision is dependent on the new counteroffer a_n , and we use the historical consumer data for a logistic regression to derive the acceptance probability dependent on the specific counteroffer.

By incorporating this behaviour into the decision model, we can derive the optimal counteroffer decision of a recommerce provider. At the end of this section, we compare the optimal strategies with the current product assessment strategy of *FLIP4NEW*.

3.6.1 Extension of the basic model's counteroffer decision

We assume in the following that the recommerce provider has no exact information about the discounted residual value δu of the individual product holder who handed in the used device. We incorporate this uncertainty about the discounted residual value with the help of a probability distribution. As the results of the previous section have shown, the product holder's final decision depends on the relation of the counteroffer a_n to the discounted residual value δu . If $\delta u < a_n$, the product holder accepts, otherwise, the counteroffer is rejected. Given the uncertain value of δu , we define the probability for the acceptance of a counteroffer as $\text{Prob}(\delta u < a_n) =: P(a_n)$. Consequently, the probability for the acceptance of a counteroffer is increasing in a_n .

For this new setting, we reconsider the counteroffer decision a_n of the recommerce provider. We extend the basic model by the probability function $P(a_n)$.³ We use this function to derive weights for the respective payoffs in the case of a counteroffer and get the following expected profit function for a counteroffer $E[\Pi^c(a_n)]$:

³We provide a detailed explanation of how the probability function can be derived from a data set of product submissions in the following.

$$E[\Pi^c(a_n)] = P(a_n)(\Delta m - a_n - c - t) + (1 - P(a_n))(-c - 2t). \quad (3.13)$$

Equation (3.13) illustrates the trade-off of the recommerce provider between the risk of losing the deal with the product holder weighted with the probability $(1 - P(a_n))$ and obtaining the desired price reduction with probability $P(a_n)$.

3.6.2 Empirical estimation of individual product holder behaviour

Product submission data

We now introduce the data set which we used to estimate the individual product holder behaviour. The data set consists of 60,000 used product submissions to *FLIP4NEW* in the period from June 2011 to November 2012. The used products are divided into six different product categories. These categories contribute the most to the profit of *FLIP4NEW*, and are *Mobile Phones* (Phones), *Tablets & E-Book Readers* (Tablets), *MacBooks* (MacBooks), *Macs & Accessories* (Macs), *Notebooks & Netbooks* (NoteNet), and *Cameras* (Cameras).

As we want to approximate the individual behaviour of the product holders when confronted with a counteroffer, we now focus on the submissions for which *FLIP4NEW* made a counteroffer. The data set contains counteroffers for 5,958 submissions of which 2030 (34.1%) were rejected by the product holders. The data for two illustrative examples are shown in Table 3.2.

Released	Category	Type	Arrived	a_j	a_n	Sold	m	Y
03/06/11	Phones	iPh. 4 16GB	06/06/11	358	304	23/06/11	379.6	1
06/06/11	Phones	iPh. 2 8GB	17/06/11	110	77	—	—	0

Table 3.2: Data for two examples of product submissions

The first line is a submission in which the product holder accepted the counteroffer. The second submission was sent back to the product holder as the offer had been rejected. The table shows on the right side the dependent variable Y which we use to define whether a counteroffer was accepted ($Y = 1$) or rejected ($Y = 0$).

Logistic regression

As the product holder's acceptance of the counteroffer is a strict "yes" or "no" decision, we conducted a binary logistic regression analysis for predicting the behaviour dependent on the specific counteroffer (Hosmer Jr et al., 2013). We used the above data set with the statistical software *IBM SPSS Statistics*.

The prediction of the product holder's behaviour is based on the counteroffer a_n as described above. An issue occurs as the different product categories contain products with a wide range of values. Thus, we have to normalise the counteroffer a_n . For this reason, we put the counteroffer a_n in relation to the provisional acquisition price a_j . We analysed two variants: (i) the ratio of the counteroffer a_n to the provisional price a_j , which we denote by ρ and interpret as the relative price difference; and (ii) the absolute price difference (α) between the counteroffer and the provisional price, i.e.

$$\rho := \frac{a_n}{a_j}, \quad (3.14)$$

$$\alpha := a_j - a_n. \quad (3.15)$$

Using these two predictor variables leads to the following probability function for the product holder's acceptance decision ($Y = 1$):

$$P(\rho, \alpha) = Pr[Y = 1] = \frac{\exp[\beta_0 + \beta_1\rho + \beta_2\alpha]}{1 + \exp[\beta_0 + \beta_1\rho + \beta_2\alpha]}. \quad (3.16)$$

Furthermore, we compared the model prediction quality with the two cases using only one predictor variable. The probability functions for these cases are defined analogously as:

$$P(\rho) = Pr[Y = 1] = \frac{\exp[\beta_0 + \beta_1\rho]}{1 + \exp[\beta_0 + \beta_1\rho]}, \quad (3.17)$$

$$P(\alpha) = Pr[Y = 1] = \frac{\exp[\beta_0 + \beta_1\alpha]}{1 + \exp[\beta_0 + \beta_1\alpha]}. \quad (3.18)$$

We carried out a binary logistic regression analysis for each product category and all three combinations of predictor variables. The results for the quality of the prediction are summarized in Table 3.3. We see that using two predictor variables for the complete data set (without differentiating product categories) leads in all to 79.4% correct predictions with regard to the acceptance decision of the individual product holder. However, the

	ρ	α	ρ and α
All	79.3%	66.3%	79.4%
Macs	83.3%	82.3%	83.3%
Table	77.5%	72.2%	77.5%
NoteNet	80.8%	77.1%	81.0%
Phones	79.6%	64.9%	79.9%
Cameras	83.9%	79.3%	84.5%
MacBooks	83.2%	81.6%	83.9%

Table 3.3: Percentage of correct predictions dependent on predictor variable combination for each product category

results show that a given change of one unit in the predictor variable α has nearly no influence on the dependent variable Y .⁴ Furthermore, comparing the model quality with only one predictor variable (see again Table 3.3) reveals that there is nearly no change in the prediction quality for the reduced regression model. Regarding, e.g., all product categories aggregated, we achieve 79.4% correct prediction with α and ρ as predictor variables and 79.3% when using only ρ . In contrast, we achieve a prediction quality of 66.3% when using only α as a predictor. In conclusion, we removed the absolute price difference α from the regression analysis and focused only on the relative price difference ρ as predictor variable for Y . Having only a single predictor variable also improves the analytical tractability. Thus, the product holder's acceptance decision Y is approximated by the logistic distribution as in Equation (3.17). With the help of the approximated parameters β_0 and β_1 , we can also describe the implied probability density function $f(\rho)$ of the scaled discounted residual value $(\delta u/a_j)$ as follows:

$$f(\rho) = \frac{\beta_1 \exp[-\beta_0 - \beta_1 \rho]}{(1 + \exp[-\beta_0 - \beta_1 \rho])^2}. \quad (3.19)$$

3.6.3 Assessment of counteroffer strategies

Optimal counteroffer decision of a recommerce provider

We rewrite Equation (3.13), which describes the expected profit for offering a counteroffer $E[\Pi^c(a_n)]$ depending on the acquisition price ρ , by inserting the approximated

⁴The odds ratio for α is close to one (e.g. for all product categories $\exp(B) = 0.999$) for most product categories. This means that the absolute price difference has only a weak predictive influence on the dependent variable Y .

probability function from Equation (3.17). To this end, we substitute the updated acquisition price of the counteroffer a_n by ρa_j . That gives us the following expected profit function for the recommerce provider:

$$\begin{aligned} E[\Pi^c(\rho)] &= P(\rho)(\Delta m - \rho a_j - c - t) + (1 - P(\rho))(-c - 2t) \\ &= \frac{\Delta m - \rho a_j - c - t}{1 + e^{-\beta_0 - \beta_1 \rho}} + \left(1 - \frac{1}{1 + e^{-\beta_0 - \beta_1 \rho}}\right)(-c - 2t). \end{aligned} \quad (3.20)$$

Using this equation, we can determine the optimal counteroffer ρ^* of the recommerce provider which maximizes the expected profit.

Proposition 5. *The unique optimal counteroffer of the recommerce provider is*

$$\rho^* := \min(\max(\rho', 0), 1) \quad (3.21)$$

with

$$\rho' = \frac{\Delta m + t}{a_j} - \frac{1 + W(e^{\beta_1(\Delta m + t)/a_j + \beta_0 - 1})}{\beta_1} \quad (3.22)$$

and $W(\cdot)$ denoting the Lambert W function.

We observe from Proposition 5 that the optimal counteroffer is dependent on the discounted achievable margin Δm , the provisional acquisition price a_j , and the transportation costs t . Furthermore, the individual behaviour of the product holder is approximated by β_0 and β_1 . The grading costs c have no influence on the optimal solution as they occur in both payoffs, i.e. they are sunk.

Comparing the above optimal counteroffer decision with the result in Section 3.5.1 of our sequential game with complete information reveals the impact of the uncertainty in the product holder's residual value on the recommerce provider's acceptance decision. In Section 3.5.1, we observed that the recommerce provider's knowledge of δu gives him complete control over the possible outcomes in the acquisition process once the used product is handed-in. Inequality (3.1) reveals that $\Delta m + t$ is the relevant decision criterion of whether the optimal counteroffer leads to an acceptance or rejection by the product holder. Using the fact that ρ is defined as $\frac{a_n}{a_j}$, we can rewrite Equation (3.22) as follows:

$$a_n = \Delta m + t - \frac{(1 + W(e^{\beta_1(\Delta m + t)/a_j + \beta_0 - 1})) a_j}{\beta_1}. \quad (3.23)$$

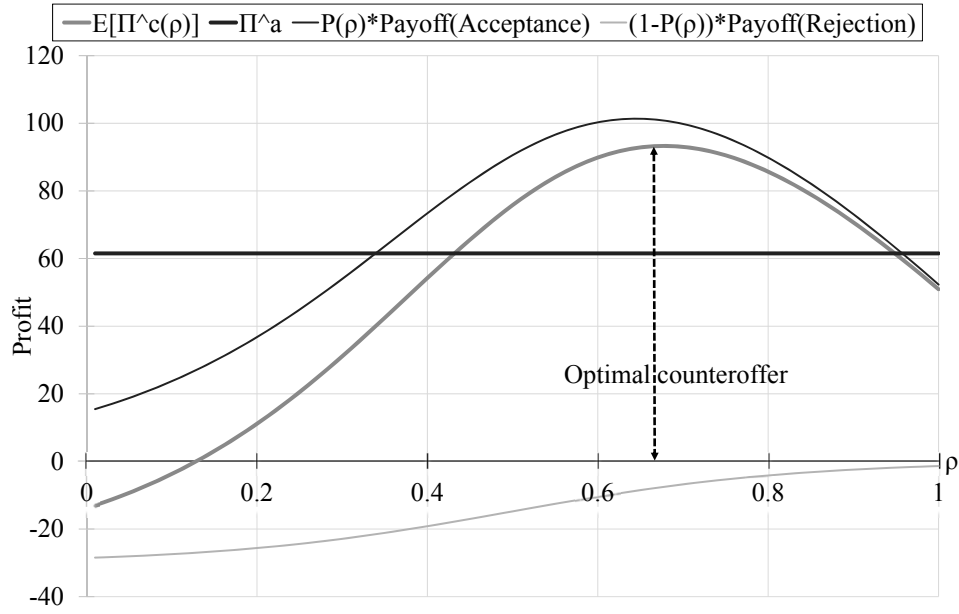


Figure 3.5: Expected profit for a counteroffer ($E[\Pi^c(\rho)]$), profit for direct acceptance of a_j (Π^a), and weighted payoffs for the counteroffer acceptance and rejection for an exemplary product submission

Equation (3.23) shows that the optimal counteroffer in the presence of uncertainty is also based on the aforementioned decision criterion $\Delta m + t$. Additionally, we observe now that this value is reduced by a term which can be interpreted as a weighted approximation of the product holder's behaviour. Hereby, the optimal counteroffer balances the risk of a rejection with the additional achievable gain by a price reduction.

Evaluating the expected profits for an optimal counteroffer $E[\Pi^c(\rho^*)]$ and comparing it with the achievable profit when accepting the provisional acquisition price Π^a shows the optimal strategy of the recommerce provider in the acquisition process. Thus, if the following inequality is satisfied

$$E[\Pi^c(\rho^*)] > \Pi^a = m - a_j - c - t, \quad (3.24)$$

it is optimal for the recommerce provider to make the counteroffer ρ^* . Otherwise, the optimal strategy is to accept the provisional acquisition price a_j . This is illustrated for a specific product submission in Figure 3.5. Additionally, this figure shows the probability weighted payoffs for the counteroffer acceptance and rejection which result in $E[\Pi^c(\rho^*)]$.

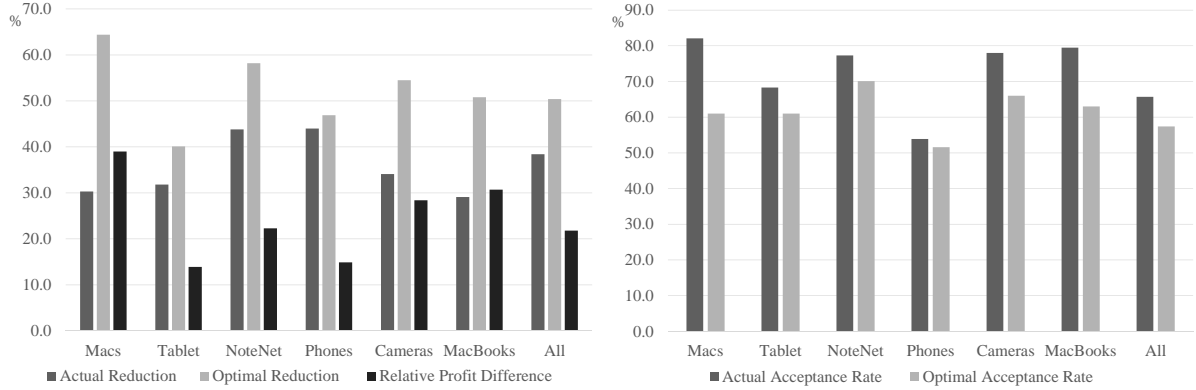


Figure 3.6: Comparison of optimal counteroffer strategy with the actual applied strategy and the resulting profit difference

Potential improvement from optimized counteroffer strategies

As already introduced in Section 3.2, *FLIP4NEW* currently handles potential counteroffers by applying a goodwill rule in case differences occur in the quality statements. *FLIP4NEW* only makes a counteroffer if the correct quality assessment reveals a price difference which is higher than a certain threshold. Furthermore, *FLIP4NEW* states that the new counteroffer equals the price for the true quality r which the grading has revealed. The profit illustration of the exemplary product submission in Figure 3.5 provides a good explanation for the applied strategy of *FLIP4NEW*. We see that offering a very low adjustment of the acquisition price with a respective low additional gain does not balance the risk of a rejection of the counteroffer in a profitable way. Thus, for a product submission with a weak deviation from the proper acquisition price a_r , it is more beneficial for *FLIP4NEW* to accept the wrong provisional acquisition price.

In the following, we compare the currently applied counteroffer strategy reflected by the available data set with the above presented strategy, based on the logistic regression model. To this end, we determine the optimal counteroffer (ρ^*) with Proposition 5 for each product submission⁵ and compared it with the proposed counteroffer by *FLIP4NEW*. Our focus is on the product submissions for which *FLIP4NEW* has offered a counteroffer as the underlying data estimation of the product holder behaviour is based on these submissions. Figure 3.6 and Table 3.4 summarize this comparison by illustrating the average counteroffers of both strategies for each product category, together with

⁵The exact data of the achieved margin (Δm) is only available for the accepted counteroffers (and afterwards sold products). Subsequently, we have approximated the achievable margin for the rejected counteroffers with the average margin for this product category based on the counteroffer a_n .

Chapter 3 - Strategic Grading in the Acquisition Process

Product Category	Macs	Tablet	NoteNet	Phones	Cameras	MacBooks	All
Actual Reduction	30.3	31.8	43.8	44.0	34.1	29.1	38.4
Optimal Reduction	64.4	40.1	58.2	46.9	54.5	50.8	50.4
Actual Accept. Rate	82.1	68.3	77.3	53.9	78.0	79.5	65.7
Optimal Accept. Rate	61.0	61.0	70.1	51.6	66.0	63.0	57.4
Relative Profit Diff.	39.0	13.9	22.3	14.9	28.4	30.7	21.8

Table 3.4: Comparison of optimal counteroffer strategy with the actual applied strategy and the resulting profit difference (in percent)

their respective counteroffer acceptance rates. Additionally, we see the average relative profit difference between the two strategies calculated with Equation (3.20).

The comparison of the strategies reveals several interesting points. First, it is clear that the optimal counteroffer ρ^* calculated with the model is significantly lower than that of the actual strategy. Thus, the approximation of the individual behaviour of the product holders suggests offering lower counteroffers. Otherwise, the trade-off between higher gains and lost acquisitions is not balanced optimally. We can conclude that even though *FLIP4NEW* applies the above goodwill rule and provides only counteroffers for cases when the price differences are sufficiently high, it weights the downside risk of a rejection of the counteroffer too low. One possible explanation for this deviation is that *FLIP4NEW* not only has a short-term view of each product submission, as our model assumes, but is interested in achieving long-term customer loyalty for generating profits from future product submissions. Thus, if a counteroffer rejection means that a product holder will not use the services of a recommerce provider in the future, the resulting losses of the rejection are higher than the losses we assume in our model. Another possible explanation for the deviation is that *FLIP4NEW* restricts itself for most product categories to counteroffers which are defined by the discrete predefined price vector a_i whereas the developed model selects the optimal counteroffer ρ^* in the interval $[0,1]$.

Additionally, the figure and table show that the optimal counteroffer ρ^* is dependent on the product categories. Interestingly, the categories with the highest optimal counteroffer ρ^* contain bulkier products (Macs: 64.4%, NoteNet: 58.2%) while for the categories which contain smaller products (Phones: 46.9%, Tablets: 40.1%) the optimal counteroffer is lower. One possible explanation for this is that the bulkiness of a returned product has an influence on the individual acceptance decision of a product holder faced with a counteroffer and fits in with the assumption on the discounted residual value

δu . Since the handling effort for taking back bulkier products is greater, the product holders are willing to accept a larger price decrease. This dependency of the multiplier for the loss in the residual value δ on the profit allocation has been already identified in the analysis of the equilibrium solution (see Section 3.5.2) and is also in line with other research concerning the bulkiness of the returned products (Wojanowski et al., 2007; Aras and Aksen, 2008; Hahler and Fleischmann, 2013).

The data set also reveals that the product category *Phones* accounts for the largest volume, i.e. 60% of the total returns. Consequently, this is probably the most important category for the business of *FLIP4NEW*. Interestingly, when regarding the differences between the currently applied and the optimal counteroffer in Figure 3.6, we observe that the difference is only 2.9% for the category *Phones*. Compared with the other categories, the gap between the two strategies is the lowest. Thus, it is reasonable to conclude that the applied strategy suits very well the most important product category. Nevertheless, the resulting profit difference between the two strategies is significant, at 14.9%.

In general, we observe that the profit difference for individual product categories amounts to up to 39%, and is 21% aggregated for all product categories. This shows how relevant the counteroffer decision is for the profitability of a recommerce provider and that there exists potential for improvement. Critical points that we must consider with regard to these results are the aforementioned limitations of our model approach about neglecting the long-term effects on customer loyalty and a possible misfit of the optimal continuous counteroffer ρ^* with the discrete price vector a_i . Furthermore, we have to take into account the achieved prediction quality of the product holder behaviour which has been about 80%.

3.7 Conclusions

Our research is motivated by a close collaboration with a recommerce provider, during which we observed newly emerging issues in the assessment of used products. We propose a basic model which describes the acquisition process between a recommerce provider and a product holder in a sequential game. We derive the optimal strategies of both players under complete information and observe that the recommerce provider can achieve most of the potential profit due to his last mover advantage. Furthermore, the equilibrium of the game illustrates the existing incentive problem between the players

concerning the correct assessment of the used products. By modifying this basic model, we evaluate levers like shifting the transportation costs towards the product holders, and additional payments for correct quality statements, and determine their effect on the optimal strategies of both players. In case of a transportation cost shift, the recommerce provider gains even more bargaining power as the payoffs of the last period will be reduced for the product holder. A bonus payment for correct grading has no effect on the optimal strategies of the players.

We extend the basic model and incorporate uncertainty about the product holder's residual value. A data set consisting of nearly 60,000 product acquisitions of a recommerce provider is used to estimate the individual product holder's return behaviour empirically. Specifically, we develop a logistic regression approach to approximate the counteroffer acceptance decision of the product holder dependent on the relative price decrease of the counteroffer. For this extended counteroffer decision model, we derive the optimal product assessment strategy of the recommerce provider. A comparison with the currently applied counteroffer strategy of the recommerce provider indicates the great potential of our newly developed strategy under the given assumptions. Furthermore, we observe the influence of the product category on the individual product holder's return behaviour. We identified the bulkiness of a product as a significant factor.

Our main research contributions to the literature are the introduction of the recommerce business to the field of reverse logistics, the identification of the recently implemented acquisition process, and the exploration of the emerging incentive problem when assessing the used products.

We see opportunities for future research in relaxing some of our modelling assumptions in our approach. We believe that a relaxation of the assumption of complete information in the sequential game can lead to further important results concerning the incentive problem. Furthermore, the derivation of the optimal strategies does not consider long-term effects on the behaviour of the product holder. In particular, if all handed-in products of product holders were to be downgraded independently of the stated quality class, this would lead to a dissatisfied customer base. Additionally, we suppose that the recommerce provider's decision about the initial price vector entails an interesting opportunity for future research.

Chapter 4

Capacity-Oriented Product Acquisition ¹

Abstract

There are several recommerce providers which are specialized in the processing of returns from individual owners of products (B2C). This business field is challenging, as events such as Christmas or the release of a new product cause high volatilities in the return volumes. Research literature has already analysed several levers that enable capacity smoothing for recommerce providers, these levers include promotions and price adjustments.

In this paper, we introduce a new lever for achieving high capacity utilization. Observations from practice reveal that recommerce providers have started to acquire batches of used products from e-commerce providers to fill their residual processing capacities. The aim of this work is to explore this new B2B acquisition market for a recommerce provider, and to analyse the underlying business decision about whether to accept or to reject a batch that is offered. We explain a current industry approach to this decision and identify additional time-dependent factors that have an impact on the profitability of this capacity lever. With the help of a basic production planning model, we are able to capture these time-dependent factors and illustrate their impact on a recommerce provider's decision to accept a batch offer, in a numerical study.

¹The research presented in this chapter is based on the paper “Capacity-Oriented Product Acquisition in Reverse Logistics”.

4.1 Introduction

Dealing with returns from individual customers is the key business of recommerce providers who specialize in the B2C market. Fluctuations of return volumes over time mean that capacity planning is a challenging task. A recent development in the practice of these recommerce providers is to expand their businesses into the B2B market and acquire complete batches of returned products from e-commerce providers, to smooth their capacity utilization. This paper explores this new business field and provides a tool for making the decision about accepting or rejecting a batch offer from the B2B market.

Many recommerce providers have a strong focus on the processing of returns from individual customers. For this reason, they operate websites through which the return process is initialized. A major need of their customers is an easy return process including the quick payment of the acquisition price once the product has been sent to the recommerce provider. Before the recommerce provider can initiate the payment, the returned product has to be tested to confirm the customer's quality statement. This process consumes a great deal of capacity, since the recommerce provider has to identify the true quality of the returned product, which can have, for example, hidden defects like water damage or unwanted switch-off behaviour. If the recommerce provider does not discover a defect, he will pay the wrong acquisition price and will resell a non-functional product; this will probably result in warranty issues with the new product owner. Additionally, as most returned products are resold to individual buyers, a recommerce provider automatically generates a separate offer for every product, with photos and a detailed description of the quality during the grading process. Possible subsequent processes of cleaning and data deletion require less work. However, a major challenge for a recommerce provider is to have the right capacity for the processing of the returns as soon as they arrive. In particular, high peaks of return volumes during the year (e.g. after Christmas or after a new product release from Apple or another major brand) demand high capacity levels. Consequently, during the summer months the demand for the services of a recommerce provider decreases significantly. This high volatility makes capacity planning a challenging task for a recommerce provider.

Several levers already exist for managing the return volume and thus achieving the right capacity utilization, and these have been analysed in detail in the research literature about reverse logistics. These levers are, for example, promotions or other adjustments to the acquisition prices (Guide et al., 2003). This paper investigates a novel business

field for a recommerce provider, which can be used as a new lever for steering capacity utilization. We consider the possibility of smoothing capacity by acquiring batches of used products that are offered by e-commerce providers like Amazon. By using these “fill-in customers”, a recommerce provider can achieve higher capacity utilization at times when the individual customer return volume is low.

During a practical collaboration with a recommerce provider from Germany,² we observed that the actual decision about the acceptance of a batch offer is based on the ratio of the expected revenue achieved by selling the used products in the batch to the capital investment needed for buying the batch. If this ratio is higher than a defined threshold, the batch offer is accepted. This approach appeals because of its simplicity. However, it has a critical weakness: it neglects time-dependent effects that occur during the time that an acquired batch is being completed. These effects are holding costs, costs of capital, and loss of value over time of the used products. The aim of this work is to analyse the influence of these effects on the decision by a recommerce provider to accept a batch offer.

To this end, we develop a simple production scheduling model. This model considers the available residual capacity for processing products from the batch over the planning horizon, and schedules the processing of each product. This allows us to capture in detail the time effects that occur for each product in the batch. Thus, a recommerce provider can evaluate the investment in a batch on a more solid basis.

To summarize, our paper makes the following contributions:

- We explore the processing of batches of used products from the B2B market as a new business field for a recommerce provider.
- We formulate a basic scheduling model to describe a recommerce provider’s production planning for an acquired batch. With the help of this model, a recommerce provider can evaluate the profitability of a batch offer.
- We uncover the impact of time-dependent costs by comparing the approach we develop with the current decision strategy of a recommerce provider.
- We provide a broad numerical study to show the impact of the key problem parameters on a recommerce provider’s decision.

²In the following, we use the anonymized company name ReComm.

The remainder of the paper is organized as follows. Section 4.2 motivates our research by introducing the problem for a recommerce provider in detail. In Section 4.3, we position our work in the research literature. We introduce our basic model with its key assumptions in Section 4.4. Section 4.5 contains the results achieved from our model. Section 4.6 summarizes our main contributions and gives directions for future research.

4.2 Capacity planning at a recommerce provider³

4.2.1 Challenges of individual customer returns (B2C market)

Most recommerce providers act as broker in the second-hand market. Their main business is to acquire used products from individual product holders and to resell them through different channels to new individual consumers. A detailed description of the business model and of the product flow for a product submission can be found in Hahler and Fleischmann (2014).

A major challenge for a recommerce provider is that the return volumes fluctuate over time. These fluctuations are caused, to some extent, by specific events like Christmas or the release of a new product. Figure 4.1 shows an example of the return volumes for the recommerce provider ReComm over time for an aggregate of five product categories (*mobiles, notebooks, Macs, tablets, cameras*). Interestingly, even though the return volume is aggregated over different product categories, significant peaks can be observed, and these match up with new product releases. In the period under consideration, we can observe two peaks. The first one corresponds to the release of the iPad 3, and the second to the release of the iPhone 5. Between these two events, the aggregated individual return volume is stable at a low level of about 400 returned devices per week. As already mentioned in Section 4.1, an individual customer expects a quick payment once he has returned his used product. Accordingly, a recommerce provider has a limited opportunity to backlog any of these returns and process them at times of lower return volumes. Thus, it is necessary for a recommerce provider to have high capacity levels available to process these individual returns in a responsive way during these peaks.

Fortunately, return peaks due to product releases or holidays such as Christmas are known in advance. Thus, successful capacity management can anticipate these fluctuations and can steer the available capacity to the right level. Known levers for capacity

³The following case description is based on a collaboration with ReComm - a German recommerce provider.

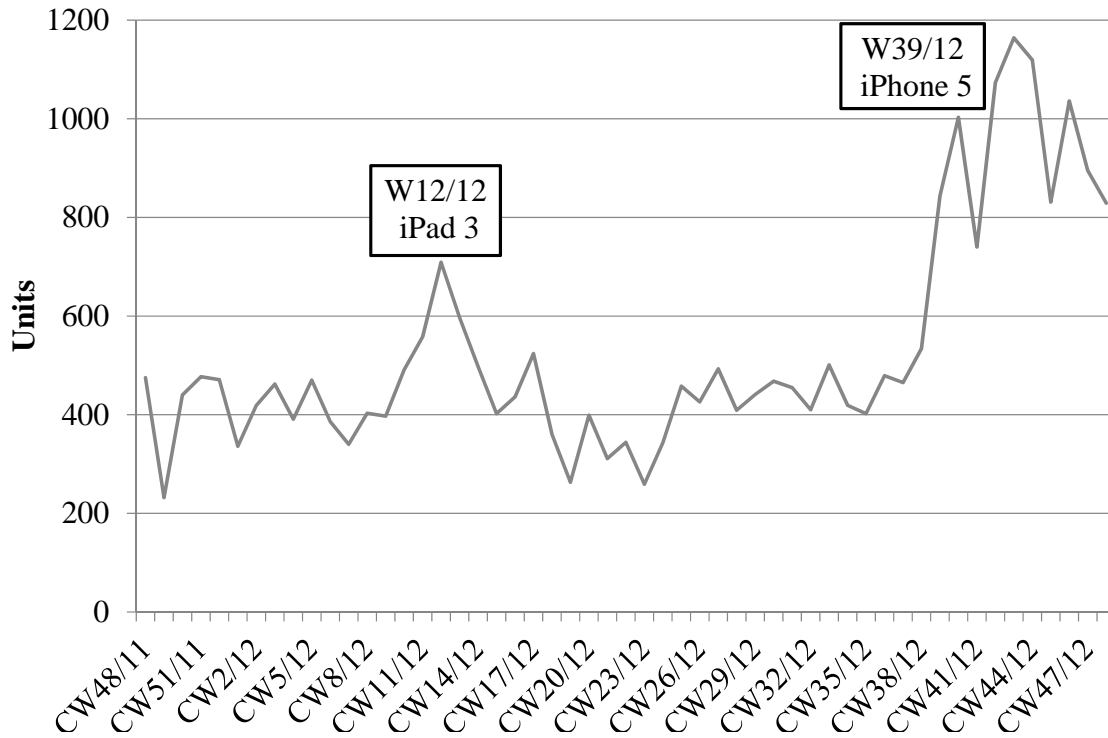


Figure 4.1: Aggregated arrivals of orders over time for ReComm

adjustments in this context are, for example, the arrangement of overtime and additional shifts at weekends, or temporary workers. However, these levers are also limited to some extent.

4.2.2 Challenges of the B2B market

Interaction on the B2B market

E-commerce providers like Amazon sell their new products on the primary market. As the result of generous return policies for their customers, product returns arise in significant numbers. Most of these returns are commercial returns or occur due to warranty issues. Regardless of whether a product is still fully functional, it may no longer be sold as new if it has already been owned by a customer. During recent years, some e-commerce providers have established separate remarketing channels for distributing these returns to the second-hand market (e.g. *Amazon Warehouse Deals*). As these channels run the risk of cannibalizing the new product sales of the e-commerce provider, they are not promoted intensively and their volume is partially bounded. Remaining

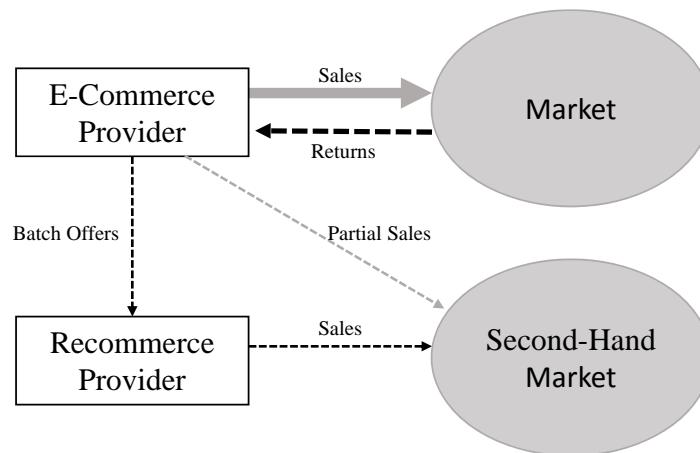


Figure 4.2: Interaction of the B2B market

stocks of returned products that an e-commerce provider will not resell through its own channels are offered to recommerce providers. These batch offers are “take it or leave it” offers for the recommerce provider, with no scope for negotiation. Thus, if the recommerce provider does not want to pay the suggested price, he will not get the batch. If a recommerce provider accepts a batch that is offered, he can sell the used products after processing, via his traditional reselling channels, to the second-hand market. Figure 4.2 sketches the interaction above described in the B2B market.

Characteristics of the B2B market

In the following section, we introduce the main characteristics of the new business field of batch offers from the B2B market, and explain how this additional lever is currently used to achieve high capacity utilization.

The size of a batch that is offered is in most cases limited by the number of products that can be shipped in a full truck load (FTL). It would be possible for a recommerce provider to buy only specific products from the batch on offer. As the price conditions for an individual purchase like this are much worse, this opportunity is usually ignored.

The products in the batch are often a mixture of products from different categories. The common denominator is that they are all consumer electronic items, and this is the major business of a recommerce provider. Furthermore, the product types and the exact number of products of each type are known in advance. Thus, there is no uncertainty about the batch size and composition.

The quality of the used products is one major driver of profitability in the reverse

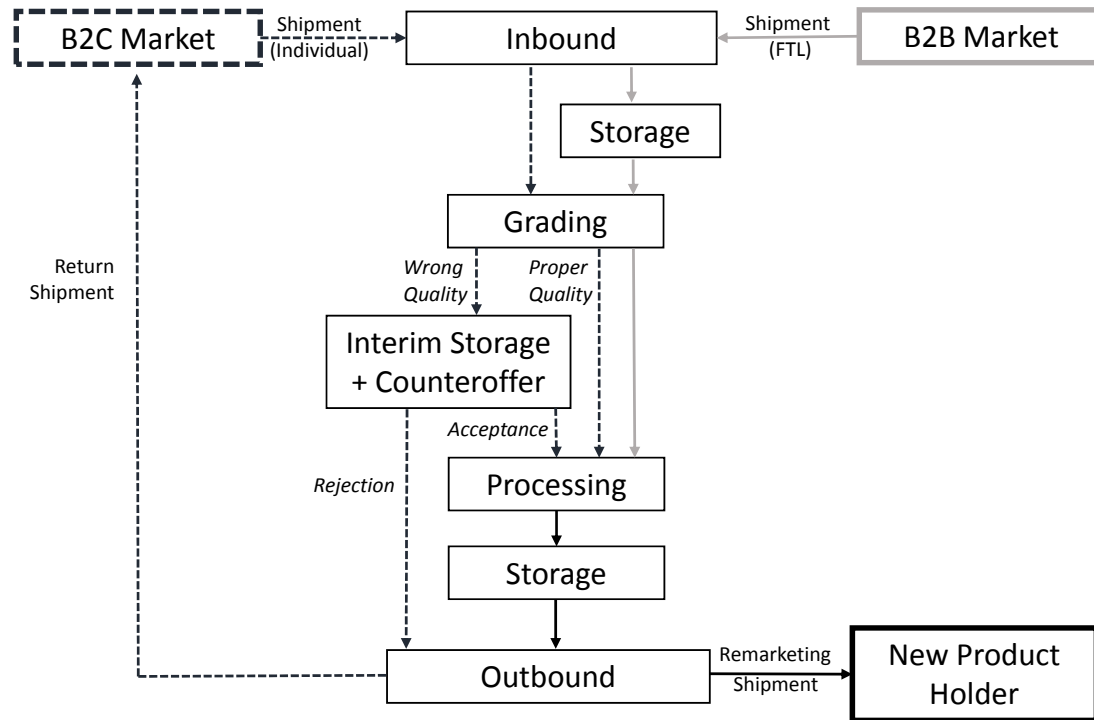


Figure 4.3: Product flow of B2C (dashed black) and B2B (grey) returns

logistics industry because it determines the necessary processing effort and the respective reselling price on the secondary market. As most used products in the offered batches are commercial returns from e-commerce providers, the quality of the products is known in advance at a limited level. The recommerce provider has, for example, information about why the product has been returned to the e-commerce provider, and can thus predict the necessary processing time and, more importantly, the achievable margin. Nevertheless, even though the e-commerce provider's quality assessment is available, the recommerce provider will grade most of the products again.

Figure 4.3 shows the product flow of B2C (dashed black) and B2B (grey) returns for a recommerce provider. We see that a used product in a batch has similar process steps to an individual return (*Grading* and *Processing*). It is only the intermediate process, for incorrect quality statements, that does not occur for these products. Additionally, products from batch offers can be stored and backlogged, in contrast to individual returns, which are processed as soon as they arrive. Thus, with regard to the processing capacity, a product from a batch offer uses the same capacity as an equivalent individual return.

Because e-commerce providers have a good knowledge of the residual value of their used products, the achievable margin for a recommerce provider for each product from an offered batch is lower than that for an individual returned product. This is the reason why the business of individual returns is the major priority for recommerce providers. Furthermore, a strong dependency on the B2B field is critical because there are only a few e-commerce providers who act as possible suppliers of batch offers.

As the exact product type, quantity, and quality are known in advance, a recommerce provider can predict his processing costs and estimate an appropriate reselling price for each product on the secondary market. ReComm's current approach for evaluating a complete batch is to estimate the expected revenues from selling each product in the batch and to relate this value to the capital investment for buying the batch. If this ratio is higher than a defined threshold, the batch offer will be accepted. One weakness of this approach is that the completion time for the used products in the batch is not considered. Thus, time-dependent costs like loss of market value, holding costs, and capital costs are neglected. Furthermore, ReComm does not consider any future offers in his batch acceptance decisions.⁴ Thus, no opportunity costs for the arrival of future offers are considered.

With respect to the loss in value of used products over time, Guide et al. (2006) were the first to consider the impact of this on the network structure. A good proof of the significance of this value loss can be found with the help of, for example, the website www.bidvoy.de. This website observes the auctions on eBay and provides the average price paid for used products for the last six months. Figure 4.4, for example, shows the price development of the *Samsung Galaxy S4* (mobile phone) for the time period March to June 2014. The average price in this period is \$280.32 with an average price decrease of \$3.51 per week, which is a value loss of about 1.25% per week.

Motivated by the observations described above of what happens in practice in the recommerce business, the aim of this paper is to analyse in detail the decision to accept an offered batch. To capture the complex time-dependent effects described above on the profitability of a batch, a key requirement is to consider the influence of the individual return volume of the B2C business field in the making of the decision. This procedure allows us to identify the major drivers for the profitability of a batch and, thus, for the batch acceptance decision.

⁴As this business field is rather new, there are no meaningful data available that could be used for the prediction of the arrivals.

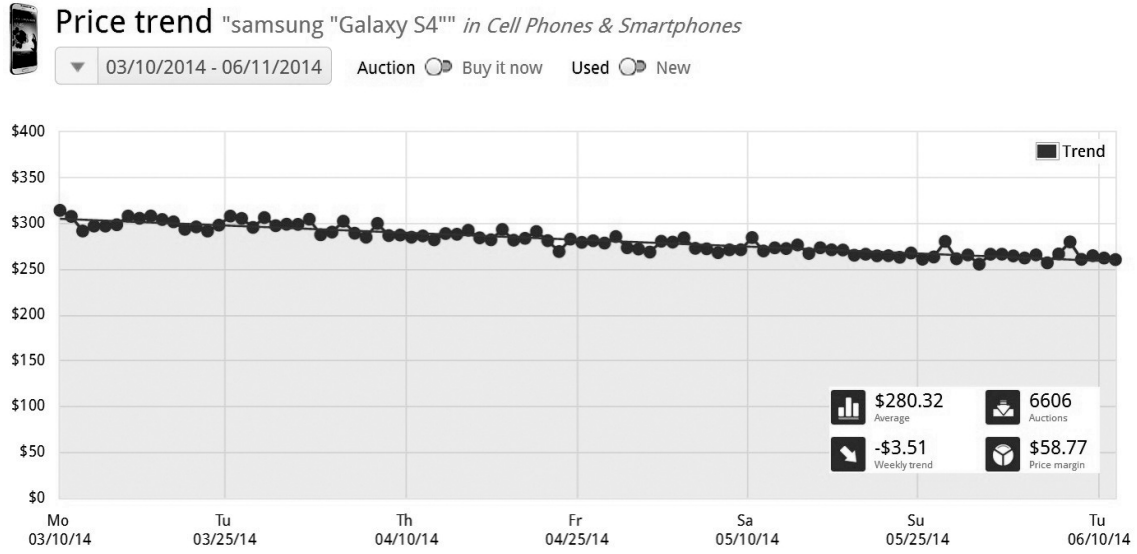


Figure 4.4: Price development of a used Samsung Galaxy S4 on the auction platform eBay (Source: <http://us.bidvoy.net>)

In addition, our interest is in the performance of the rule currently applied by ReComm to reach a decision. To this end, we evaluate the decision that would currently be reached and compare the result with the approach we have developed, which takes into account the exact throughput time of each product in the batch.

Additionally, a recommerce provider faces the problem that future batch offers are potentially more profitable than the current offer. A batch offer that has already been accepted may block the capacity to accept a more profitable batch offer in the future. We consider this trade-off in our analysis of the acceptance decision for a batch that is currently being offered. For this reason, we analyse how the expectation of a future batch offer influences the acceptance decision of a recommerce provider like ReComm.

4.3 Literature

Several issues with respect to capacity management in closed-loop supply chains or reverse logistics have already been analysed, even though this research field is rather new. Guide et al. (1997) were among the first to introduce capacity-planning techniques for remanufacturing, and to study the performance of these techniques in this context. Recent reviews with a strong focus on production planning are those of Akcali and Çetinkaya (2011), Junior and Filho (2012), and Steeneck and Sarin (2013). These reviews

reveal important aspects, which help us to position our research in the literature.

The first aspect is that previous research into closed-loop supply chains has a strong focus on so-called hybrid systems. These systems have the property that they can manufacture new products as well as processing returned products. Thus, customer demand can be satisfied by manufactured or remanufactured products. Important business decisions for these systems are, for example, the integration of the returns into the production process, and the control of the serviceable inventory. The business we consider, that of a recommerce provider, differs since a recommerce provider does not manufacture new products. Hence, a large amount of the closed-loop supply chain literature does not refer to our problem setting.

The second important aspect is the specific business decision that is analysed in this context. Focal points of acquisition management are, for example, the quantity and the pricing decisions with respect to the used products. Economies of scale in transportation and set-up costs for remanufacturing mean that the quantity decision in reverse logistics can be similar to the EOQ in traditional forward supply chains (Schrady, 1967; Richter, 1996a,b). Zikopoulos and Tagaras (2007) recently investigated the optimal lot size decision for a non-hybrid system. They determined the optimal procurement and production lot sizes from collection sites in a reverse logistics setting that is very similar to our problem. Nevertheless, there is one major difference: in our setting, the quantity decision is not taken by the recommerce provider. The product quantities are defined exogenously when the e-commerce provider offers the batch. Looking at the research literature that has a focus on pricing decisions, we come to the same conclusion. In our practice setting, the recommerce provider does not influence the price at which a batch batch is offered.

A significant link to the research literature on reverse logistics is made with by our modelling approach. We develop a production planning model that is used for scheduling the processing of the acquired products in an optimal order. Similar planning models for non-hybrid systems have been introduced by Jayaraman (2006), Franke et al. (2006), Souza (2010), and Doh and Lee (2010).

Jayaraman (2006) emphasizes that the balancing of supply with demand is a complicated task. He develops an approach that optimizes the number of products to be acquired, disassembled, disposed of, and remanufactured in each time period. The resulting aggregate production planning model is used on data from a company that remanufactures mobile telephones. For the same business context, Franke et al. (2006) introduce

their linear optimization model for the planning of production programmes and remanufacturing capacities. Their approach is characterized by a detailed representation of the different disassembly processes that may occur in this industry. Souza (2010) introduces the remanufacturing practice of Pitney Bowes to motivate his aggregate planning model. He emphasizes that an explicit consideration of the available capacity is one benefit of his approach. Doh and Lee (2010) extend the existing production planning models and introduce set-up costs and times in the planning problem. To this end, they develop a mixed integer programming model and propose solution algorithms.

The model we develop differs from the above models, especially in its consideration of the impact of time. Since we are assuming that time-dependent costs have a strong influence on the profitability of an offered batch, we consider in the decision-making, in addition to inventory holding costs, the loss in the value of a product over time and the capital cost. To this end, our aggregate planning approach discounts future cash flows, and thus determines the optimal net present value (NPV) of the investment in an offered batch. We refer to Lawrence (1991) for an example of an NPV application in a scheduling environment.

With respect to the business decision we are considering to accept an offered batch, an additional research stream is relevant for our approach. The order acceptance and scheduling problem in a traditional forward supply chain has a similar structure to the decision we are considering. Slotnick and Morton (2007) describe the problem as “the trade-off between the revenue brought in by a particular order, and its claim to processing resources, which may delay other jobs and incur penalty costs or discounts on the price paid to the manufacturer”. A recent review of this field is given by Slotnick (2011). The present paper considers a similar trade-off in the reverse logistics business. The major difference between the two trade-offs is in the downside risk. In the order acceptance problem, a manufacturer may incur high penalty costs because of missed due dates, whereas in our offer acceptance problem, longer processing times lead to costs due to the loss in value over time and inventory holding and capital costs.

To sum up, to our knowledge there is no research literature considering the offer acceptance problem in reverse logistics. Thus, our main contribution to the literature is the identification and analysis of the B2B market as a new capacity management lever for a recommerce provider. To this end, we consider a non-hybrid remanufacturing system in which the recommerce provider does not decide on the size or price of an offered batch.

4.4 Basic scheduling model

The following model considers a single batch offer made to a recommerce provider. The profitability of accepting the batch is evaluated by an operational schedule that considers the time span within which each product in the batch will be prepared for the resale market. The operational schedule takes into account the amount of capacity used by the individual returns. In this way, this approach allows us to capture in detail the time-dependent effects that occur, such as the loss in value over time. Before introducing the model formulation, we present our model assumptions and provide a short discussion.

4.4.1 Assumptions

Operational factors

1. Assumption: *The planning horizon is finite and consists of T periods.*

For determining the profitability of a batch, the planning horizon of the model has to cover the time until the whole batch is processed. This finite time is dependent on the available excess capacity for processing the batch, the batch size, and the capacity that is used to process the products in the batch.

Depending on the level of detail, a period can be considered as a working day or a whole working week. In our numerical analysis, we consider an aggregated setting in which the time periods are weeks.

2. Assumption: *The available processing capacity in a planning period c_t is deterministic and is known in advance for every time period t .*

We consider in our model only one aggregated capacity restriction for processing, as our focus is not on analysing the influence of flexible capacity. Nevertheless, this basic formulation can be extended without much effort. Thus, in the following we use the expression “processing” for all the operations that are necessary to prepare a product for the secondary market.

3. Assumption: *The return volumes from individual customers are deterministic and are known in advance for the whole planning horizon T . The respective capacity utilization for these returns is u_t .*

In the short term, a recommerce provider obtains good knowledge by observing the registrations on his website. Additionally, if the recommerce provider uses a tracking system for parcels, then even the exact arrival dates of the individual product submissions at his facilities are known. We assume that other levers for steering the volume of

individual returns like promotions or price adjustments, are planned with a longer time horizon and are included in u_t . Thus, these levers are not captured separately. In the long term, the return volumes from individual customers will be to some level uncertain, as the predicted return volumes are less accurate over a longer period. To this end, we will analyse the sensitivity of the results to this parameter in the following numerical studies.

4. Assumption: *The processing of a used product requires a capacity p_k with $\mathcal{K} = 1, \dots, K$ describing the product category k . The cost for one capacity unit is g_k .*

As a batch consists of different products, different processing steps such as data deletion and cleaning have to be taken before the products can be resold. Thus, the capacity utilization for a product is dependent on the specific workload, which we assume to be dependent on the product category k .

The costs of the processing are also dependent on the specific product category k . The largest part of these costs is determined by the working time for grading and processing. Other costs result from the consumption of specific materials that are necessary for the operations, etc.

5. Assumption: *Holding costs occur that depend on the product category h_k . The rate for the cost of capital is d .*

For as long as a product of the batch has not been processed, it has to be kept in stock. Thus, a product causes holding costs, which are dependent on its volume. Holding costs include the rent for the required space, equipment, materials, and labour to operate the space. Additionally, they may include insurance and security for the inventory. The interest on capital invested in the inventory is not part of this rate.

For discounting the future payments achieved by reselling the used products, we use the discount rate d of the recommerce provider. This return rate describes the opportunity cost of capital, which is the amount that could be earned on an investment in the financial markets with a similar risk.

Batch properties

6. Assumption: *The offered batch of used products costs b and consists of a deterministic amount of different products described by x_k , $k = 1, \dots, K$.*

The recommerce provider always acquires the complete batch. The price of the batch is b . Buying specific products from the offered batch is not possible at a reasonable price.

Second-hand market properties

7. Assumption: We use a parameter a_k that describes the value of a used product of category k . The achievable revenue for selling a product after processing is based on this value. The percentage margin for each product category is m_k . Additionally, the products in the batch lose value over time. The percentage loss in value is described by δ_{kt} .

Even though a recommerce provider always acquires the complete batch, we consider a parameter for the value of each product individually. This allows an easier calculation of the achievable reselling revenues, loss in value over time, and holding costs, which are all based on the product value.

4.4.2 Linear programming formulation

The idea of the modelling approach is to schedule the processing of each used product in the offered batch within the planning horizon. In this way, the model captures the capacity utilization of the individual return volume and the time-dependent costs (loss in value, holding costs and capital costs) in the calculation of the profitability of the batch. We decided to use a linear programme formulation because of its simple adaptability, applicability, and tractability in practice.

Index sets:

Symbol Description

t	Set of time periods $\mathcal{T} = \{1, \dots, T\}$
k	Set of product categories $\mathcal{K} = \{1, \dots, K\}$

Variables:

Symbol Description

Y_{kt}	Number of products of category k processed in period t
Z	Objective value

Parameters:

Symbol Description

c_t	Available total capacity in period t
u_t	Utilized capacity for individual product submissions in period t
x_k	Number of products of category k in the relevant batch offer
b	Price of the offered batch
a_k	Monetary value of one product of category k
d	Cost of capital per time period
m_k	Expected percentage margin for one product of category k
δ_{kt}	Multiplier for discounting the loss in value over time for a product of category k
h_k	Holding cost for a product of category k
p_k	Capacity usage for processing one product of category k
g_k	Costs of one processing unit for product category k

Objective function:

$$\max Z = -b + \sum_k \sum_t \left(Y_{kt} (a_k m_k (1 - \delta_{kt}) - p_k g_k) - (x_k - \sum_{t'=1}^t Y_{kt'}) a_k h_k \right) / (1 + d)^t \quad (4.1)$$

Constraints:

$$\sum_k Y_{kt} p_k \leq c_t - u_t \quad \forall t \in \mathcal{T} \quad (4.2)$$

$$\sum_t Y_{kt} \leq x_k \quad \forall k \in \mathcal{K} \quad (4.3)$$

$$Y_{kt} \geq 0 \quad \forall k \in \mathcal{K}, t \in \mathcal{T} \quad (4.4)$$

The objective function (4.1) maximizes the achievable profit of the batch offer. To this end, the profit function considers the acquisition costs for the batch, the sales revenues, the holding costs for inventories, the processing costs, and the capital costs for the investments. As the future payments are discounted at the cost rate for capital, the objective function determines the NPV for the investment in the batch offer. The optimal solution of the linear programme schedules the processing times of the products in the batch in the most efficient way, resulting in the maximum NPV. Consequently,

if this NPV is positive ($Z > 0$), the optimal decision of the recommerce provider is to accept the offered batch.

Constraint (4.2) ensures that the capacity restriction is satisfied. As already discussed in Section 4.2, individual customer returns will always be prioritized for processing. In this way, the key requirement of the B2C business - a quick return process with a responsive payment - will be achieved. We define the excess capacity that is available for processing a batch offer in a time period t as $c_t - u_t$. Thus, only the capacity that is not used for processing individual customer returns can be used for processing products from the batch offer. Constraint (4.3) ensures that there cannot be more products processed and sold than are contained in the batch offer. Constraint (4.4) ensures the non-negativity of the decision variable Y_{kt} .

4.5 Numerical study

In the following, we use the proposed basic model to analyse the problem of a recommerce provider when confronted with a batch offer. First, we introduce a basic data set for an offered batch, which is used as a starting point for most scenarios. Then we highlight the current practice approach of the recommerce provider ReComm, which we use as a benchmark.

We begin the numerical study with a simplified setting in which the individual return volume and the available total capacity are constant over time. Thus, the recommerce provider has a static capacity utilization resulting in a static residual capacity for dealing with the batch offer. This simplification allows us to reveal the isolated influence of the basic problem parameters on the profitability of the offer. To this end, we set up a test bed based on a full factorial design.

After revealing the isolated influence of the problem parameters, we consider several extended scenarios. First, we demonstrate the impact of the level of planning detail on the acceptance decision. Then, we consider a dynamic return pattern and show its influence on the batch profitability. Finally, we further develop the basic scheduling model approach and consider how information on future batch offers influences the acceptance decision for a given batch offer.

4.5.1 Basic data set

At the beginning of our numerical study, we intend to reveal the isolated influence of the key problem parameters. To this end, our basic data set consists of a batch with only one product category⁵ ($k = 1$) as listed in Table 4.1. As we begin with static

k	x_k	a_k	c	p_k	g_k	d	h_k	m_k	δ_k
1	400	45	550	1	9.5	0.43%	0.077%	1.3	0.01

Table 4.1: Basic data set

illustrations without changes in the parameters over time, the notation of the basic case is without the time index t . The selected parameter values for the basic case reflect the market conditions for a German recommerce provider like ReComm, and are discussed in more detail in what follows.

To define the total available capacity of the recommerce provider, we consider the individual return volume over the five most important product categories for ReComm in the time period from CW 41 of 2011 to CW 49 of 2012. The average return volume was roughly 500 units per week. As a recommerce provider covers minor fluctuations in return volume without any capacity adjustments, we assume that the total capacity is 10% higher than the average return volume. Thus, for the static individual return case, the total capacity is set at 550 units per week.⁶

Besides the total capacity c , the operational factors are the capacity usage for processing one product (p_k), the processing costs per unit (g_k), the capital costs (d), and the holding costs (h_k). The capacity usage is one unit ($p_1 = 1$), as we assume that the batch consists of products similar to the individual returns. The processing cost of one capacity unit is 9.5 Euros, and depends on the hourly earnings of the worker doing the processing. As recommerce providers are rather small and risky enterprises that specialize in products with short-life-cycles, we assume an annual capital cost rate of 25% (and so a weekly rate of $d = 0.43\%$) (Khadjavi, 2005). The holding cost rate is comprised of three different parts. These are tax ($\approx 1\%$), insurance ($\approx 2\%$), and storage ($\approx 1\%$). Consequently, the annual holding cost rate is about 4% (and so the weekly rate is $h_k = 0.077\%$).

⁵In Section 4.5.4, we consider the impact of multiple product categories on the acceptance decision of a recommerce provider.

⁶In the numerical study, we consider a wide range of different capacity levels, because the results depend strongly on this parameter.

The batch properties for the basic data set are the size and the price of the batch. We consider an offer of 400 products ($x_1 = 400$). Thus in the basic case the total batch uses less than 75% of the total weekly available capacity ($c = 550$). Consequently, the batch size is not large compared to the total capacity. The batch price b is defined in the following by the product value a_k and the product amount x_k as $b := \sum_k x_k a_k$. The product value in the batch is $a_1 = 45$ and is, in general, lower than the value of the individual returns.

The secondary market is defined by the percentage margin (m_k) and the loss in value of the used products (δ_k). The average percentage margin of a data set of individual returns is about 1.6 to 1.8. As already described in the problem setting, the percentage margin for a product in a batch offer is significantly lower. This is because of the market experience of an e-commerce provider. In our basic case, we use a percentage margin $m_1=1.3$. The loss in value over time for a product is very relevant, especially for electronic consumer goods. In general, a good approximation in the recommerce business is 1% loss in value per week. To this end, we consider a one per cent loss in value based on the value in the first period.

4.5.2 Current practice approach of ReComm (ROI)

ReComm's current approach to evaluating a complete batch is to calculate the expected revenues from selling all products of the batch and to relate this value to the capital investment for buying the batch. If this ratio is higher than a defined threshold, the batch offer will be accepted. A typical threshold value in the recommerce business is in the range of 6–10%, with the value depending on the capital structure of the recommerce provider. In the following, we use 8% as the critical threshold for the current acceptance decision. The choice of the specific threshold value can be used to capture the effect of time-dependent costs - however, only in an aggregated fashion. In particular, the current practice approach uses the same threshold value for all batches.

In the following, we call this approach the *return on investment* (ROI) approach. The

formal definition of the ROI with its calculation for the basic data set is

$$\begin{aligned}
 \text{ROI} &:= \frac{\sum_k x_k (a_k (m_k - 1) - p_k g_k)}{\sum_k x_k a_k} \\
 &= \frac{400 \cdot (45 \cdot (1.3 - 1) - 9.5)}{400 \cdot 45} \\
 &\approx 8.9\% > 8\%.
 \end{aligned} \tag{4.5}$$

The ROI is higher than the defined acceptance threshold of 8%, and consequently ReComm would acquire the batch offer for the basic data set.

4.5.3 Impact of the key problem parameters

To reveal the impact of the different problem parameters, we carried out a numerical study with a full factorial design. For the available excess capacity, we examined five different scenarios (5%, 10%, 15%, 20%, and 25%). For all other parameters of the basic data set, we considered a 20% increase and a 20% decrease of the parameter value. In total, this resulted in 10,935 different scenarios. The optimal solution for each scenario was based on the optimal schedule of processing all products in the batch as soon as possible. This solution structure occurs because here we consider only one product category in the batch.

In total, the NPV approach suggests that the offered batches should be accepted in 7,275 (66.53%) scenarios. Comparing the NPV approach with the ROI approach shows that they lead to the same result in 8,329 scenarios (76.1%). In 703 (6.5%) scenarios, the current approach accepts a batch that is not profitable with respect to the NPV. On the other hand, profitable batches are refused by the current practice in 1,903 scenarios (17.4%).

In the following, we illustrate and discuss the impact of the key problem parameters. We begin with the parameters that are mainly under control of the recommerce provider (operational factors). After this, we consider the properties of the batch and of the second-hand market. To this end, we calculate and illustrate the average of the NPV over all the scenarios mentioned above, with one of the problem key factors being fixed at one of its admissible values.

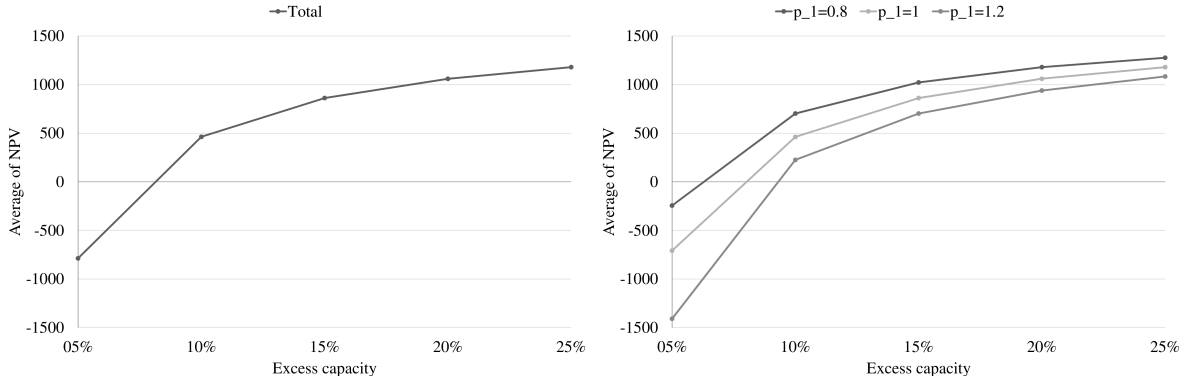


Figure 4.5: Impact of excess capacity (left) and capacity usage (right) on the average NPV

Operational factors

The left side of Figure 4.5 illustrates the impact of the available excess capacity on the NPV. We observe that the NPV increases strictly as excess capacity increases. For low levels of excess capacity, the NPV is negative. Thus, an offered batch is no longer profitable. In total, the range of the NPV is from -786.73 (at 5% excess capacity) to 1,179.65 (at 25% excess capacity). Curiously, we observe from the definition of the ROI in Equation (4.5) that the influence of the individual returns on capacity is neglected in the current acceptance decision. For this reason, the decision-making in the ROI cannot take account of the time-dependent costs. This property is the fundamental difference between the NPV approach we have developed and the ROI approach that is currently applied.

The strong impact of excess capacity on the NPV can be explained by the time-dependent costs. For lower levels, the total processing time for the complete batch increases, which inflates the time-dependent costs we are considering, and reduces the profitability of the batch. This time-cost effect is reduced for higher levels of excess capacity. As our aim is to explore this time-cost effect in relation to the other major problem parameters, we consider in the following how the NPV depends on the excess capacity.

On the right side of Figure 4.5, we see the influence on the NPV of a 20% decrease or increase in the capacity usage of a product (p_k). The progression of the NPV for the base case ($p_1 = 1$) is nearly the same as on the left side. For a lower capacity usage per product ($p_k = 0.8$), we observe that the time-cost effect is flatter, and that the NPV increases. We can make the opposite observation for a higher capacity usage ($p_1 = 1.2$).

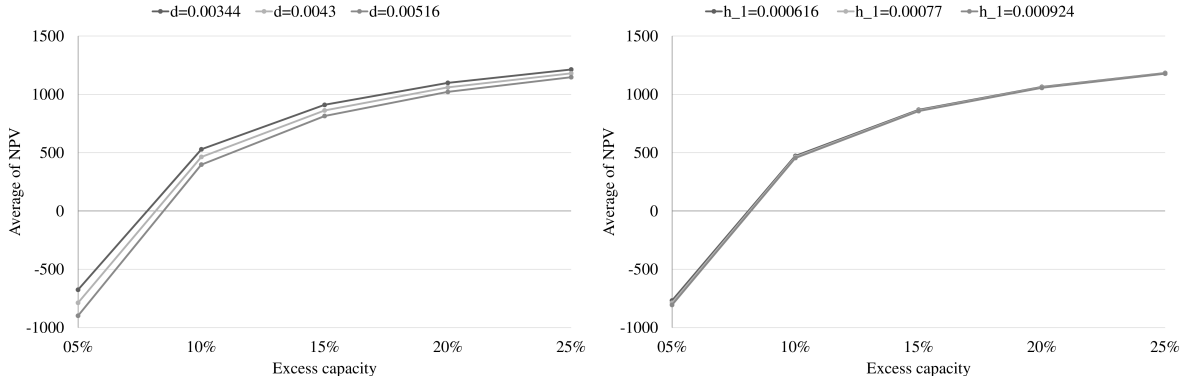


Figure 4.6: Impact of cost of capital (left) and holding costs (right) on the average NPV

The impact of the capacity usage per product on the NPV is two-sided. On the one hand, the capacity usage increases which leads to longer processing times for the complete batch. On the other hand, this parameter is linked to the objective function of the processing costs which also increase with p_k .

As our aim is to make the influence of each problem parameter comparable, we consider the acceptance rate for all scenarios in the decreased and increased parameter constellation. Therefore for the capacity usage, we consider the acceptance rate over all scenarios in which $p_1 = 0.8$ and compare this rate with the respective rate for $p_1 = 1.2$. The batch acceptance rate for $p_1 = 0.8$ is 73.11%, and it is 60% for $p_1 = 1.2$. We define the difference between the two rates as the “NPV acceptance impact”: the NPV acceptance impact of capacity usage is $73.11\% - 60\% = 13.11\%$. In the following, we use this measure to compare the influence of all the problem parameters.

The decision in the current approach (ROI) is also influenced by the capacity usage per product. Analogously, we use the same measure as for the NPV and call it the “ROI acceptance impact”. In a direct comparison for all the scenarios in which $p_1 = 1.2$ ($p_1 = 0.8$), the ROI is higher than the threshold of 8% in 33.3% (77.7%) of the scenarios. Thus, the ROI acceptance impact is 44.4%. The comparison with the NPV acceptance impact reveals that the ROI approach is too sensitive to this parameter.

Two further operational factors for a recommerce provider are the cost of capital and the holding costs. Figure 4.6 illustrates the influence of the increase and decrease in these parameters on the average NPV.

We observe that the impact on profitability is very limited for both parameters. The impact of the holding costs is even lower than that of the cost of capital. Additionally, we observe the time-cost effect for lower excess capacity levels. Again, the impact of

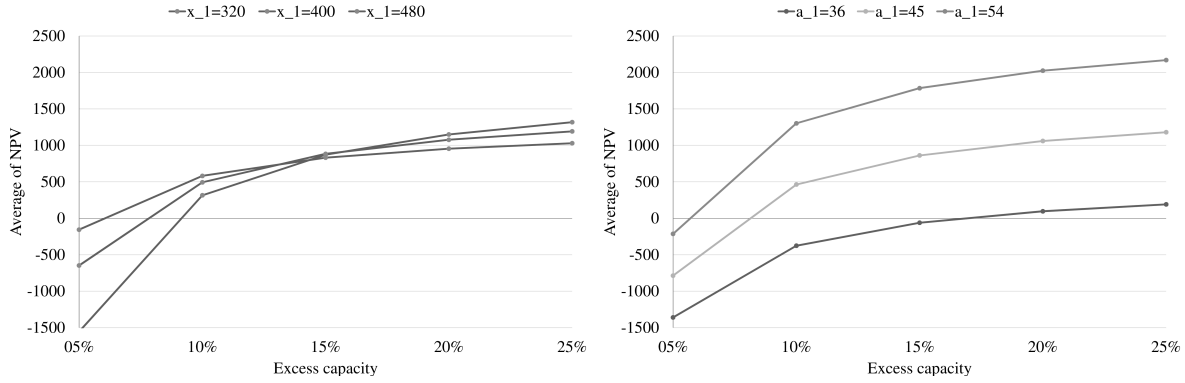


Figure 4.7: Impact of the batch size (left) and the product value (right) on the average NPV

both factors increases if the processing time of the complete batch is longer. Using the acceptance impact measure defined above for both parameters confirms our observation. The acceptance impact of the holding costs is 0.28% and that of the cost of capital is 3.49%.

Neither holding costs nor capital costs are included directly in the calculation of the ROI. These costs are only captured indirectly through the target ROI. Thus, these parameters have no influence on the current approach.

Batch properties

The left side of Figure 4.7 illustrates the impact of different batch sizes (x_1), and the right side the impact of different product values (a_1); together these define the total batch price. For the batch size, we observe that the NPV of the batch may be greater or smaller for a larger batch size. The turning point is at about 15% excess capacity.

The explanation for this observation is that the NPV is not a relative value that is based on an investment volume. In general, bigger batches have the potential to result in higher NPVs. However, they also require a higher investment. This influence is not captured in the NPV calculation. The progression for the different batch sizes observed in Figure 4.7 again appears because of the time-cost effect. In general, the total batch processing time increases with the batch size. Thus, for low levels of excess capacity, the time-cost effect outweighs the potential of a higher NPV due to a larger batch size.

Interestingly, if we consider the impact of the batch size on the current approach, we observe that there is no change in the ROI. This is due to the fact that the ROI is a relative measure based on the number of products.

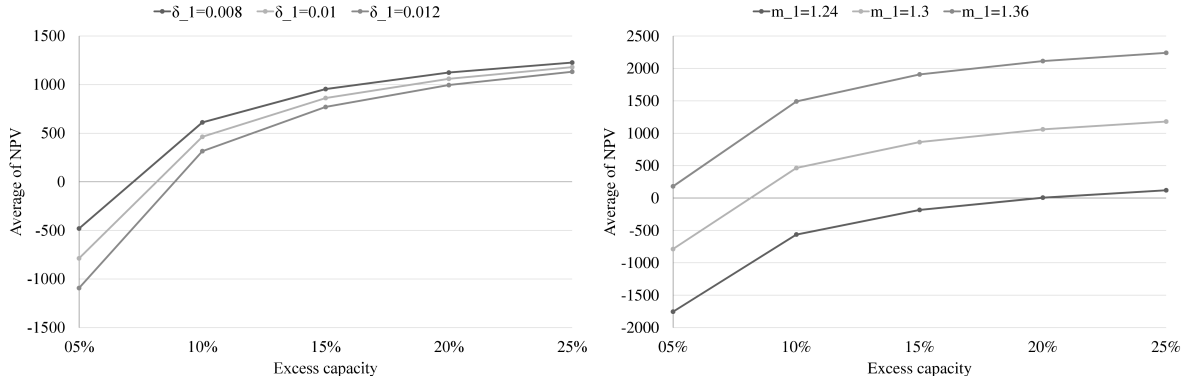


Figure 4.8: Impact of the loss in value over time (left) and the product margin (right) on the average NPV

The graphs for the different product values on the right side of Figure 4.7 show an interesting progression that is also based on the absolute NPV measure. For any specific excess capacity level (ec), the difference in the NPVs for two adjacent buying prices is the same (i.e. $NPV(a_1 = 54, ec = 10\%) - NPV(a_1 = 45, ec = 10\%) = NPV(a_1 = 45, ec = 10\%) - NPV(a_1 = 36, ec = 10\%)$). This difference increases with higher excess capacity levels. This observation arises from the fact that the product value is linked to the product margin. Thus, a higher product value implies, in addition to a higher total batch investment, the potential for a higher absolute NPV. For low levels of excess capacity, the longer processing time of the batch reduces this potential relatively. This is caused by the fact that the time-dependent costs are all relative measures based on the product value.

Comparing the influence of the product value on the ROI shows that the acceptance rate changes from 33.3% for $a_1 = 36$ to 77.7% for $a_1 = 54$ (ROI acceptance impact=44.4%). The acceptance rates of the NPV are 42.55% and 87.27%. The ROI changes for this parameter because the processing costs are fixed, whereas the margin increases or decreases depending on the product value. From the acceptance rates calculated above, we can already observe that the product value is a strong driver for the NPV acceptance impact, with a figure of 44.72%, whereas the NPV acceptance impact for the batch size is moderate, with a figure of 13.11%.

Second-hand market properties

Figure 4.8 shows the last two parameters that we consider in our numerical study. On the left side, we see the impact of a change in the loss in value over time. The

curve progression is comparable to that for the cost of capital and the holding costs. We observe again that the influence increases for longer processing times (lower excess capacity levels). The acceptance impact of this parameter is 7.93%, which reveals that the loss in value over time has a stronger influence than changes in the cost of capital and the holding costs. As the ROI approach does not consider any time-dependent costs, the loss in value over time has no influence on the ROI-based acceptance decision.

The right side of Figure 4.8 illustrates the impact of the product margin on the NPV. We observe a similar progression to that shown for the product value, although for the product margin the rate of increase in the differences is less than that for the product value. This is due to the fact that the product margin does not influence the total investment amount for the batch. Additionally, the holding costs are not linked to the product margin.

The product margin is also considered in the ROI of the decision rule that is currently applied. For this parameter, the acceptance rate differs from 11.1% for $m_1 = 1.24$ to 88.8% for $m_1 = 1.36$ (ROI acceptance impact = 77.7%). When compared with the acceptance rates for the NPV approach (35.47% and 91.74%), we find that the ROI is too restrictive, especially for low product margins.

Table 4.2 summarizes the NPV and ROI acceptance impact of all the parameters under consideration. A comparison of the NPV acceptance impact for the product margin with

Parameter	x_1	a_1	p_1	d	h_1	m_1	δ_1
NPV accept. impact	13.11%	44.72%	13.11%	3.49%	0.28%	56.27%	7.93%
ROI accept. impact	-	44.44%	33.33%	-	-	77.78%	-

Table 4.2: NPV and ROI acceptance impact of all parameters under consideration

that for all the other parameters reveals that product margin has the strongest impact on the batch acceptance decision, with a figure of 56.27%. Additionally, we observe from Table 4.2 that the ROI approach is only influenced by three parameters, namely product value, capacity usage and product margin. Interestingly, the three parameters considered in the ROI approach also have the major impact on the decision based on the NPV. The direct comparison of the parameters shows that the impact of the product value is nearly the same for the two approaches, whereas the acceptance impacts for the capacity usage and the product margin are too strong. To conclude, even though the simplicity of the ROI approach means that all time-dependent costs are ignored, the major drivers for the batch acceptance decision are included.

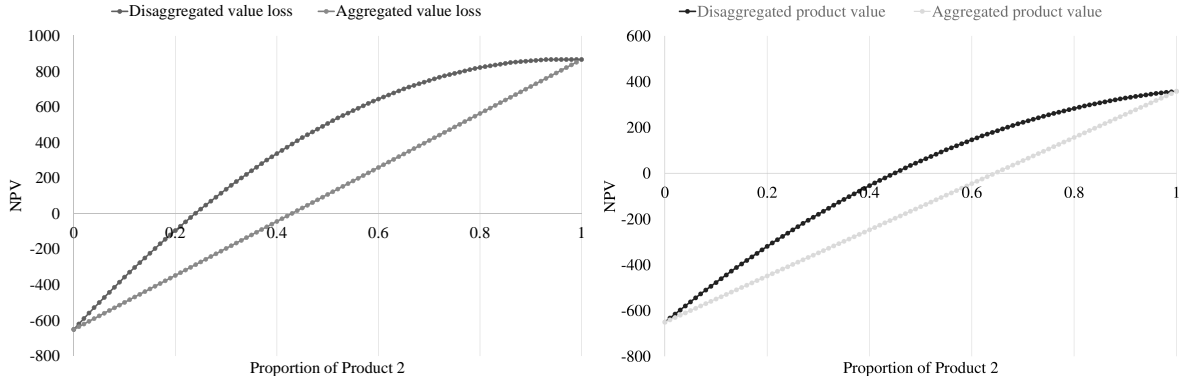


Figure 4.9: Impact of aggregated and disaggregated loss in value pattern (left) and product value (right) on the NPV

4.5.4 Extended scenarios

In this section, we look at selected scenarios to illustrate further influences on the batch acceptance decision. As full factorial numerical studies for these scenarios include too many parameters, we restrict our focus for these illustrative scenarios. The selected scenarios are typical for a recommerce provider like ReComm, even though they are very stylized.

Impact of level of detail in the planning process

Until now, we have considered only one product category k in our numerical study. In the following, we consider batches that consist of different product categories. Our aim is to illustrate the impact of this heterogeneity on the NPV and to emphasize the importance of the right level of detail in the planning. To this end, we consider again the data set for the basic batch offer in a setting in which the excess capacity is low (5%). Additionally, the batch consists now of two product categories (1 and 2). These product categories differ in one property. As our aim is to reveal the impact of the level of detail, we compute the NPV with an explicit consideration of the property. In what follows, we will call this calculation “disaggregated”. This result will be compared with the NPV in which the weighted average of the product properties is used (“aggregated”).

Figure 4.9 shows two scenarios in which one product property differs between Category 1 and 2. On the left side, the loss in value over time is different. Products in Category 1 have the loss in value over time of the basic data set, which is $\delta_1 = 0.01$. The products in Category 2 have no value loss, i.e. $\delta_2 = 0$. As described above, we determine the NPV for

the case in which the two product categories are considered individually (disaggregated). Additionally, we calculate the weighted average of the property (e.g. if the proportion of products in Category 2 is 50%, the weighted average for the loss in value is 0.005). Figure 4.9 shows the NPV according to the proportion of products in Category 2 in the complete batch. Thus, for proportions of 0% and 100% both calculations lead to the same NPV. In between, we observe that the disaggregated calculation outperforms the aggregated.

This significant effect on the NPV is the result of a different scheduling of the products. In the disaggregated case, the products without a loss in value over time are processed at the end of the planning horizon, whereas in the aggregated case, the scheduling does not differ between the product categories, as the loss in value property is not considered separately.

On the right side of Figure 4.9, we see a second scenario for a disaggregated and aggregated NPV calculation. In this example, the product value differs between the product categories ($a_1 = 45$, $a_2 = 60$). In this case, the earlier scheduling of the product category with the higher product value leads to the difference in the NPV, because the holding costs, loss in value over time, and cost of capital can be reduced.

We observe from these scenarios that the exact scheduling of the different products has a significant impact on the NPV, and that the level of detail in planning may have an influence on the batch acceptance decision. A disaggregated view is recommended, especially for batch offers that have NPVs around zero, since hidden scheduling potential may be present. The aggregated approach evaluates the offered batch in too conservative a way.

Profitability of an offered batch over time

So far, our focus in the numerical study has been to reveal the impact on the acceptance decision of isolated problem parameters and the level of detail in the planning. To this end, we have considered a static individual return volume. In the following, we relax this property, and illustrate the impact of a dynamic individual return pattern on the NPV. We consider the same batch offer as in the basic data set, for different time periods. The capacity usage due to individual returns is based on a real-life data set from ReComm that describes the aggregated returns of five product categories over more than 35 time periods. In this time span, we observe, for example, a peak in the return volume caused by the introduction of the new iPad 3 in CW 12. The left side

Chapter 4 - Capacity-Oriented Product Acquisition

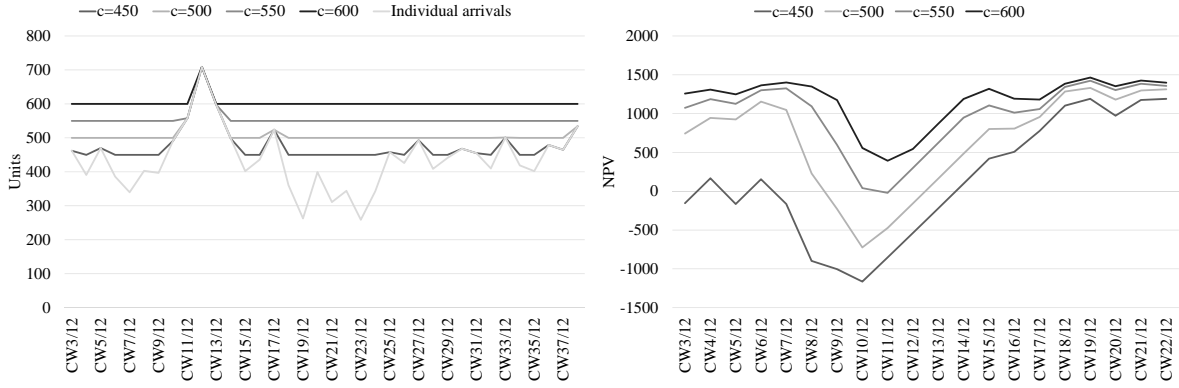


Figure 4.10: Order arrivals for different capacity levels over time (left) and respective NPVs for arriving batches, depending on total available capacity (right)

of Figure 4.10 shows the dynamic arrivals of the returns. Additionally, four different total capacity levels are illustrated, which we consider in the following. As already mentioned, one key requirement of the B2C market is that an individual return has to be processed immediately and cannot be backlogged. To capture this issue, we assume in the following calculations that the capacity level is adjusted as follows $c_t := \max(c, u_t)$. Thus, individual return peaks are always processed in the period in which they occur, independent of the regular total capacity level. This generous capacity rule cuts out some of the individual returns, which leads to a specific average return volume \bar{u} for each capacity level. These are listed with the resulting average excess capacity, acceptance rate and profitability in Table 4.3. We see that the average return volume \bar{u} increases for

	$c=450$	$c=500$	$c=550$	$c=600$
Average return volume \bar{u}	401.6	424.4	430.3	431.6
Average excess capacity	10.76%	15.12%	21.76%	28.07%
Average acceptance rate	55%	80%	95%	100%
Average profitability	129.5	653.6	978.8	1168.3

Table 4.3: Average return volume, excess capacity, acceptance rate, and profitability depending on capacity level

higher total capacity levels. At the same time, the average excess capacity also increases. This results in an increase of the average acceptance rate and the profitability for higher total capacity levels.

The right side of Figure 4.10 shows the calculated NPVs for an offered batch over time for each capacity level. We see that the individual return pattern has a direct influence on

the NPV of an offered batch. In particular, the return peak due to the release of the new iPad 3 leads to a great decrease in the NPV for all capacity levels, even though we use the generous capacity adaptability described above. The average acceptance rate for each capacity level resulting from the respective NPVs on the right side of Figure 4.10 reveals that, independent of the time period, the batch offer is always accepted for the highest capacity level ($c = 600$). For all other capacity levels, the dynamic individual return pattern that we are considering causes at least one batch to be rejected. A comparative calculation in which the average excess capacity level from Table 4.3 is assumed to be static over time shows that the offered batch will be accepted for every capacity level, as the NPV is always positive ($\text{NPV}(c = 450) = 334.8$, $\text{NPV}(c = 500) = 1112.7$, $\text{NPV}(c = 550) = 1346.3$, $\text{NPV}(c = 600) = 1414.2$). Additionally, the significant difference between the static NPVs and the average dynamic NPVs confirms the strong effect of a dynamic individual return pattern.

From the average profitability and acceptance rates listed in Table 4.3, we observe that, particularly for lower levels of capacity, a capacity level increase has a high impact on these two rates; for higher levels of capacity, the impact of the decrease is less.

We conclude from this numerical illustration that a dynamic individual return pattern has a strong influence on the NPV, and thus on the batch acceptance decision. Additionally, we have observed that the available capacity level in the period under consideration is a major driver of the acceptance rate. The ROI of the current approach completely neglects the dynamics of the return volume. The ROI for the batch under consideration is higher than the specific threshold, and therefore, the batch will always be accepted.

Expectations of future batch offers

A key assumption of the previous sections is that the recommerce provider does not take into account possible future batch offers in his acceptance decision. In general, future batch offers should affect the acceptance decision of a current batch. Future batches have the potential to be more profitable because, for example, they may arrive at time with greater excess capacity or they may consist of more profitable used products. An offer that has already been accepted may block the available capacity, making the future batch offer unprofitable. We relax the key assumption in the following, and illustrate how the expectation of a future batch offer influences the acceptance decision for a

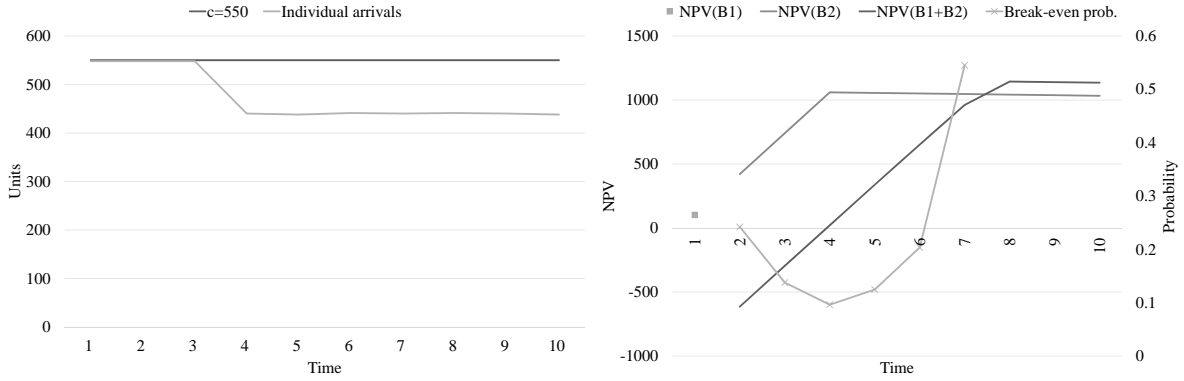


Figure 4.11: The individual return scenario under consideration (left) and the respective NPVs for current and future batch offers (right)

current batch offer.⁷

For the illustration, we examine a very stylized setting in which the recommerce provider has to decide about a batch offer based on the basic data set arriving at Period 1. The recommerce provider is faced with a peak in individual returns. This return peak is an example of the situation for a recommerce provider when new products are released by Apple or other major brands. We assume that the peak blocks the total capacity for 3 periods i.e. the excess capacity is 0% in Periods 1, 2, and 3. Afterwards, the recommerce provider has an excess capacity of 20% available for the rest of the planning horizon. The left side of Figure 4.11 shows the capacity setting in this scenario.

The NPV of the basic batch offer in Period 1 is 102.1, and is shown as $NPV(B1)$ on the right side of Figure 4.11. If the recommerce provider did not take into account any future batch offers in his acceptance decision, he would accept this offer, as the NPV is positive. In the following, we illustrate the impact of a possible future offer on the current acceptance decision. To this end, we determine the NPV⁸ for the same batch offer for the following periods. This is illustrated in Figure 4.11 as $NPV(B2)$, assuming that the recommerce provider rejects the first offer in Period 1 ($B1$). Additionally, $NPV(B1 + B2)$ is the NPV assuming that the recommerce provider accepts the current batch offer ($B1$) and a future batch offer with the same characteristics in one of the following periods.

⁷During our practical cooperation with the recommerce provider, there were no meaningful data available that could be used for the approximation of future offer arrivals. Thus, in the following, we can only illustrate how the recommerce provider's expectations of a future batch offer influence his decision.

⁸All NPVs for the future batch offers are discounted to the current time period ($t = 1$).

We observe that $NPV(B2)$ is greater than $NPV(B1)$ for each time period and increases until the end of the peak (Period 4). The later arrival of the batch means that the negative influence of the peak in the individual returns is lower. After Period 4, $NPV(B2)$ slowly decreases as the return on the investment is achieved later.

$NPV(B1 + B2)$ is negative until Period 4 and increases until Period 8. Initially, the low excess capacity results in long processing times, which make the additional investment in the second batch unprofitable. As the influence of the return peak is reduced for later arrival periods, $NPV(B1 + B2)$ increases. Starting from Period 5, $NPV(B1 + B2)$ is higher than $NPV(B1)$ (338.82). Thus, if the recommerce provider accepts the current batch, it is optimal to buy an offered second batch in or after Period 5. Starting from Period 8, the acceptance of the first batch in Period 1 no longer has an influence on the processing of the second batch. For that reason, $NPV(B1 + B2)$ slowly decreases as does $NPV(B2)$.

Using the resulting NPVs that depend on the recommerce provider's acceptance decision, we can derive a break-even probability. This describes the optimal decision rule of the recommerce provider. The probability defines the expectation for a future batch offer for which a recommerce provider is indifferent about accepting or rejecting the batch in the first period. If there is only one possible future offer, the break-even probability p is determined as follows:

$$\begin{aligned} p \cdot NPV(B2) &= NPV(B1) + \max(p \cdot (NPV(B1 + B2) - NPV(B1)), 0) \\ \Leftrightarrow p &= \frac{NPV(B1)}{NPV(B2) - \max(NPV(B1 + B2) - NPV(B1), 0)}. \end{aligned} \quad (4.6)$$

Thus, if the recommerce provider's expectation of a future batch offer is higher than the break-even probability p , it is optimal to reject the current batch offer and wait for a more profitable future one. Otherwise, the optimal decision is to accept the current batch. For the scenario we have considered, the break-even probability p is shown on the right side of Figure 4.11.⁹ The peak at the beginning means that the break-even probability is very low (for Periods 2 to 6 is lower than 25%).

To conclude, the scenario we have considered illustrates the dependencies of the current acceptance decision on potential future batch offers. As observed in the previous section, the timing of an offered batch has a strong impact on its profitability, because of the

⁹In our scenario, p is defined from Period 2 until Period 7 because it is only for these periods that $NPV(B2) > \max(NPV(B1 + B2) - NPV(B1), 0)$.

time-dependent costs. Additionally, we see that the acceptance of multiple batches utilizes significantly more excess capacity which also reduces the profitability of the investment in the batches. We derive the break-even probability p that balances the underlying trade-off in the current acceptance decision of a recommerce provider. In our stylized setting, we consider only one future batch offer, and assume that it is identical to the currently offered one. In general, a recommerce provider has to take into account multiple potential future batch offers that can have different compositions.

4.6 Conclusions

Our research is motivated by a close collaboration with a recommerce provider whose major acquisition market is the B2C market. We observed that this recommerce provider had started acquiring batch offers from e-commerce providers in order to smooth his capacity utilization. We introduce this new problem setting of B2B offers into the field of reverse logistics, with its underlying complexity, to study the acceptance decisions for offered batches. We develop a scheduling approach that includes time-dependent costs and discounts future payments with the cost rate for capital. Thus, our approach optimizes the NPV of an investment in an offered batch. Additionally, we present the ROI approach that is currently applied to decide on an offered batch.

A broad numerical study is used to reveal the impact of the key problem parameters on the batch acceptance decision. A comparison with the ROI approach that is currently applied shows that the major drivers in the batch acceptance decision are included, even though the simplicity of the approach means that all time-dependent costs are ignored. Nevertheless, the ROI approach recommends a different acceptance decision to the NPV approach for 23.9% of the scenarios in our numerical study.

We use extended scenarios to illustrate three further factors in the batch acceptance decision. First, the necessity of a detailed product scheduling approach is illustrated by exploring the level of detail in planning. The scenarios we consider show that the level of detail is crucial for batch offers that achieve NPVs of around zero, since hidden scheduling potential may be present. Second, we investigate the influence of a dynamic B2C return volume on the batch acceptance decision. The key result is that the batch acceptance rate is significantly lower for the dynamic return volume than it is for the static return volume. Third, we extend the model approach we have developed and introduce the impact on the acceptance decision of expectations about future batch

offers. We observe that, as well as the timing of an offered batch, the acceptance of multiple batches influences the profitability of the offered batches. We illustrate the trade-off in the current acceptance decision of a recommerce provider by determining the break-even probability for which a recommerce provider is indifferent about whether to accept or reject the batch in the first period.

Our main contribution to the research literature is the introduction of the new area of B2B offers to the field of reverse logistics, and the detailed analysis of a complex batch acceptance decision.

We see opportunities for future research in extending the scheduling approach by incorporating capacity flexibilities. This would allow the cost of an increase in the capacity level to be balanced against the potential gains from the quicker processing of an offered batch. Additionally, the impact of the B2B market on the decisions about capacity size for a recommerce provider is also a promising area for future research.

Appendix A

Proofs of Chapter 2

Proof of Proposition 1.

Equation (2.4) shows that the decision for an optimal a_i^* with $i \in \mathcal{I}$ is independent of all the other elements in \mathcal{I} . Thus, we have I one-dimensional optimization problems. Let $i \in \mathcal{I}$. We determine the maximum of the profit function (2.4) in the two parts of the domain distinguished in (2.3).

Case 1: $d \leq \frac{ha_i}{k}$. From Equation (2.4), the necessary first-order condition for an inner maximum $\partial \Pi^d(d, a)/\partial a_i = 0$ results in $a_i^*(d) = \frac{1}{2}p_i + \frac{1}{3}\frac{kd}{h}$. This condition is also sufficient since $\partial^2 \Pi^d(d, a)/\partial a_i^2 = -\frac{2\phi_i h}{U_i} < 0$, and thus $\Pi^d(d, a)$ is concave in a_i . a_i^* satisfies the condition for Case 1 if and only if $d \leq \frac{3hp_i}{4k}$. Otherwise, we have a corner solution at $a_i = \frac{kd}{h}$.

Case 2: $d > \frac{ha_i}{k}$. From Equation (2.4), the necessary first-order condition for an inner maximum $\partial \Pi^d(d, a)/\partial a_i = 0$ yields two possibilities: $a_{i1} = 0$ and $a_{i2} = \frac{3}{4}p_i$. As $\frac{\partial \Pi^d(d, a)^2}{\partial^2 a_i}(a_{i1}) = 0$ and $\frac{\partial \Pi^d(d, a)^3}{\partial^3 a_i}(a_{i1}) = \frac{2p_i \phi_i h^3}{U_i k^2 d^2} > 0$, a_{i1} is a saddle point. a_{i2} maximizes the profit, because $\frac{\partial \Pi^d(d, a)^2}{\partial^2 a_i}(a_{i2}) = -\frac{3\phi_i h^3 p_i^2}{4U_i k^2 d^2} < 0$. a_{i2} satisfies the condition for Case 2 if and only if $d > \frac{3hp_i}{4k}$. Otherwise, we have again a corner solution at $a_i = \frac{kd}{h}$.

Continuity of the profit function at $a_i = \frac{kd}{h}$ completes the proof. \square

Proof of Proposition 2.

We consider the profit function in (2.6) and proceed as in the proof of Proposition 1.

Case 1: $\tilde{d} \leq \frac{\eta ha}{k}$. From Equation (2.6), the necessary first-order condition for an inner maximum $\partial \Pi^c(\tilde{d}, a)/\partial a = 0$ results in $a^*(\tilde{d}) = \frac{1}{2} \frac{\sum_i \frac{\phi_i}{U_i} p_i}{\sum_i \frac{\phi_i}{U_i}} + \frac{1}{3} \frac{k\tilde{d}}{\eta h}$. This price maximizes the profit, because $\partial^2 \Pi^c(\tilde{d}, a)/\partial a^2 = -\sum_i \frac{2\eta \phi_i h}{U_i} < 0$. a^* satisfies the condition for Case 1 if

and only if $\tilde{d} \leq \frac{3}{4} \frac{\eta h}{k} \frac{\sum_i \frac{\phi_i p_i}{U_i}}{\sum_i \frac{\phi_i}{U_i}}$. Otherwise, we have a corner solution at $a = \frac{\tilde{d}k}{h\eta}$.

Case 2: $\tilde{d} > \frac{\eta h a}{k}$. From Equation (2.6), the necessary first-order condition for an inner maximum $\partial \Pi^c(\tilde{d}, a)/\partial a = 0$ yields two possibilities: $a_1 = 0$ and $a_2 = \frac{3}{4} \frac{\sum_i \frac{\phi_i p_i}{U_i}}{\sum_i \frac{\phi_i}{U_i}}$. As $\frac{\partial \Pi^c(\tilde{d}, a)^2}{\partial^2 a}(a_1) = 0$ and $\frac{\partial \Pi^c(\tilde{d}, a)^3}{\partial^3 a}(a_1) = \frac{2h^3 \sum_i \frac{\phi_i p_i}{U_i}}{k^2 \tilde{d}^2} > 0$, a_1 is a saddle point. a_2 maximizes the profit, because $\frac{\partial \Pi^c(\tilde{d}, a)^2}{\partial^2 a}(a_2) = -\frac{3h^3 (\sum_i \frac{\phi_i p_i}{U_i})^2}{k^2 \tilde{d}^2 \sum_i \frac{\phi_i}{U_i}} < 0$. a_2 satisfies the condition for Case 2 if and only if $\tilde{d} > \frac{3}{4} \frac{\eta h}{k} \frac{\sum_i \frac{\phi_i p_i}{U_i}}{\sum_i \frac{\phi_i}{U_i}}$. Otherwise, we have again a corner solution at $a = \frac{\tilde{d}k}{h\eta}$.

Continuity of the profit function at $a = \frac{\tilde{d}k}{h\eta}$ completes the proof. \square

Proof of Proposition 3.

Assume that $d^*(a)$ is an optimal network density for the given price vector a . In addition, assume that $d^*(a) > ha_1/k$. From (2.4) and (2.3), the profit of the decentralized collector $\Pi^d(d, a)$ for that case is

$$\Pi^d(d, a) = \sum_i \frac{(p_i - a_i)\phi_i(ha_i)^3}{3U_i k^2 d^2} - \frac{F}{d^2 \pi}. \quad (\text{A.1})$$

From (A.1), we see that if $\sum_i \frac{(p_i - a_i)\phi_i(ha_i)^3}{3U_i k^2} - \frac{F}{\pi} > 0$, $\Pi^d(d, a)$ is strictly decreasing in d . This contradicts the optimality of $d^*(a)$. Thus, $\sum_i \frac{(p_i - a_i)\phi_i(ha_i)^3}{3U_i k^2} - \frac{F}{\pi} \leq 0$. In that case, $\Pi^d(d, a)$ is negative and strictly increasing in d . Thus, the optimal network density $d^*(a)$ is infinite.

Assume now that $d^*(a) \leq ha_1/k$. Let $j = \max\{i | d^*(a) \leq ha_i/k\}$. From (2.3) and (2.4), we have

$$\Pi^d(d, a) = \sum_{i=1}^j (p_i - a_i) \frac{\phi_i}{U_i} (ha_i - \frac{2}{3}kd) + \sum_{i=j+1}^I \left((p_i - a_i) \frac{\phi_i(ha_i)^3}{3U_i k^2 d^2} \right) - \frac{F}{d^2 \pi}. \quad (\text{A.2})$$

Solving for the necessary first-order condition results in

$$d^*(a) = \left(\frac{3F/\pi - \sum_{i=j+1}^I \frac{(p_i - a_i)\phi_i h^3 a_i^3}{U_i k^2}}{\sum_{i=1}^j \frac{(p_i - a_i)\phi_i k}{U_i}} \right)^{\frac{1}{3}}. \quad (\text{A.3})$$

The condition is also sufficient since $\frac{\partial^2 \Pi^d(d, a)^2}{\partial^2 d} = \frac{2}{d^4} \left(\sum_{i=j+1}^I \frac{(p_i - a_i)\phi_i h^3 a_i^3}{U_i k^2} - \frac{3F}{\pi} \right)$ is negative according to (A.3) since $d^*(a)$ is positive. Thus, $d^*(a)$ is optimal. \square

Proof of Proposition 4.

We show that the values of a and d calculated in the proposed algorithm are monotone increasing. Since according to Proposition 1, the values of $a_i^*(d)$ are also bounded this assures the convergence of the algorithm.

From Proposition 1, we see that $a_i^*(d)$ is monotone increasing in d . Furthermore, $a_i^*(d) = \frac{3p_i}{4}$ is constant for $d > \frac{3hp_i}{4k}$. Inserting this constant value in (2.16) yields

$$d = \left(\frac{3F/\pi - \sum_i \mathbb{1}_{\{\frac{3hp_i}{4k} < \hat{d}\}} \frac{27}{256} \frac{\phi_i h^3 p_i^4}{U_i k^2}}{\sum_i \mathbb{1}_{\{\frac{3hp_i}{4k} \geq \hat{d}\}} \frac{(p_i - a_i) \phi_i k}{U_i}} \right)^{\frac{1}{3}}, \quad (\text{A.4})$$

which is monotone increasing in a_i . □

Appendix B

Proof of Chapter 3

Proof of Proposition 5.

The first order derivative of Equation (3.20) is

$$\partial E[\Pi(\rho)]/\partial \rho = \frac{((-1 - \beta_1 \rho) a_j + (\Delta m + t) \beta_1) e^{-\beta_0 - \beta_1 \rho} - a_j}{(1 + e^{-\beta_0 - \beta_1 \rho})^2} \quad (\text{B.1})$$

and the first-order condition $\partial E[\Pi(\rho)]/\partial \rho = 0$ results in

$$\rho' = \frac{\Delta m + t}{a_j} - \frac{1 + W(e^{\beta_1(\Delta m + t)/a_j + \beta_0 - 1})}{\beta_1} \quad (\text{B.2})$$

with $W(\cdot)$ denoting the Lambert W function. As $e^{(\cdot)} > 0$, the Lambert W function is unique, and thus ρ' is also unique.

Considering Equation (B.1), we observe that $(-1 - \beta_1 \rho) a_j + (\Delta m + t) \beta_1$ and $e^{-\beta_0 - \beta_1 \rho}$ are both decreasing in ρ as β_1 is always positive in our setting¹. Since furthermore, $e^{-\beta_0 - \beta_1 \rho} > 0$, it follows that $\partial E[\Pi(\rho)]/\partial \rho$ is positive for $\rho < \rho'$ and negative for $\rho > \rho'$. Thus, Equation (3.20) is unimodal with its maximum value at ρ' .

As the counteroffer decision is only defined for ρ in the interval $[0,1]$, the optimal counteroffer ρ^* is ρ' in case $0 \leq \rho' \leq 1$. Otherwise, due to the unimodality of Equation (3.20), the optimal counteroffer ρ^* is 1 (0) for the case that $\rho' > 1$ ($\rho' < 0$). \square

¹The ratio of the counteroffer to the provisional acquisition price ($\rho = a_n/a_j$) is positively correlated with the counteroffer acceptance decision of the product holder.

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